Labor Misallocation Across Firms and Regions[*][†]

Sebastian Heise
Federal Reserve Bank of New York

Tommaso Porzio
Columbia University, NBER, and CEPR

October 9, 2023

Abstract

We develop a frictional labor market model with multiple regions and heterogeneous firms to study how frictions impeding labor mobility across space affect the joint allocation of labor across firms and regions. Bringing the model to matched employer-employee data from Germany, we find that spatial frictions generate large misallocation of labor across firms *within* regions. By shielding firms from competition for workers from other regions, spatial frictions allow low productivity firms to expand, reducing aggregate productivity. Overall, we show that taking into account the characteristics of the local labor market is important to quantify the aggregate losses from spatial frictions.

JEL: J6, O1, R1

[*]We thank Michael Peters for a very insightful discussion of the paper. We also thank Ufuk Akcigit, Andy Atkeson, Gharad Bryan, Paco Buera, Julieta Caunedo, Lorenzo Caliendo, Kevin Donovan, Niklas Engbom, Ben Faber, Pablo Fajgelbaum, Tarek Hassan, Gregor Jarosch, Kyle Herkenhoff, Fatih Karahan, Pete Klenow, David Lagakos, Rasmus Lentz, Paolo Martellini, Mushfiq Mobarak, Ben Moll, Simon Mongey, Todd Schoellman, and Jonathan Vogel for very useful comments that improved the paper. We have also benefited from the reactions of several seminar and conference audience, including participants at the NBER SI EFMPL, NBER Growth, Berkeley, Columbia, LSE, UBC, UCLA, UPenn, University of Toronto. Rachel Williams provided excellent research assistance. The views and opinions expressed in this work do not necessarily represent the views of the Federal Reserve Bank of New York. This study uses the weakly anonymous Establishment History Panel (Years 1975 - 2014) and the Linked-Employer-Employee Data (LIAB) Longitudinal Model 1993-2014 (LIAB LM 9314). 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 remote data access. The study also uses data made available by the German Socio-Economic Panel Study at the German Institute for Economic Research (DIW), Berlin. Neither the original collectors of the data nor the archive bear any responsibility for the analyses or interpretations presented here.

[†]Heise: 33 Liberty Street, New York, NY 10045, email: sebastian.heise@ny.frb.org. Porzio: 665W 130th St, New York, NY 10027, email: tommaso.porzio@columbia.edu.

1 Introduction

In many countries, there are large differences in productivity and real wages across regions.[1] This fact suggests the presence of frictions, such as moving costs, that prevent worker migration towards more productive regions. Labor is thus misallocated across space, and removing barriers to labor mobility could generate large aggregate gains (Gollin et al. (2014), Herrendorf and Schoellman (2018)).

Focusing on spatial gaps in isolation, however, misses that there are large productivity differences across firms even *within* narrow geographic markets (Lentz and Mortensen (2012), Lindenlaub, Oh, and Peters (2022)). In this paper, we argue that taking into account this within-region heterogeneity, and more broadly the local labor market frictions, is important. It changes the quantitative estimates of the costs of spatial frictions and alters the mechanisms through which they operate. Overall, we show the importance of studying labor misallocation across space and firms jointly.

The intuition behind our argument is straightforward. Given the within-region heterogeneity, the impact of reallocating workers across regions depends on the firms these workers end up at. If there are large labor market frictions limiting workers' ability to climb the local job ladder, migrants might get stuck at unproductive firms even if they move to high productivity regions. At the same time, due to the within-region heterogeneity, worker migration is not necessary to close regional gaps. Local reallocation of workers to better firms might be sufficient. Spatial frictions may nonetheless play a key role, but through a different mechanism. They limit workers' job opportunities and thus shield firms from competition from other regions, allowing low productivity firms to survive. Removing spatial frictions could thus improve the allocation of labor even within region.

To formalize these arguments, and to quantify the extent to which local heterogeneity shapes the aggregate costs of spatial frictions, we develop a general equilibrium framework that embeds frictional labor markets as in Burdett and Mortensen (1998) within a multi-region economy. We estimate the model with matched employer-employee data from Germany, a country with large regional variation in wages and productivity. We find that the aggregate gains from reducing spatial frictions hinge on the extent to which they affect the allocation of labor across firms. In particular, two economies could look identical in terms of their wage or productivity gap between regions, yet the aggregate gains from removing spatial frictions could vary dramatically between the two dependent on their local labor market frictions.

In the first part of the paper, we use micro data from the German Federal Employment

[1] Examples are the Italian South versus North or the East versus West of Germany.

Agency to document three sets of facts, which motivate our focus on the joint allocation of labor across firms and regions and guide the ingredients of our model.

First, we use the Establishment History Panel (BHP), a 50% sample of all establishments in Germany, to document that there is a large wage gap between East and West Germany, but also substantial heterogeneity across firms *within* these regions. In principle, it would be possible to close the East-West wage gap by just reallocating labor within East Germany towards higher-wage firms.

Second, we use the Linked Employer-Employee Data (LIAB) to show that East Germans get very large wage increases when moving West, suggesting substantial gains from regional integration, but that workers also experience sizable wage gains for job-to-job moves within-region. Thus, frictions hindering within-region mobility could be as costly as those limiting migration towards high productivity regions.

Third, we show that workers switch jobs mostly locally and exhibit home bias (i.e., workers have a preference for their home region), leading to a job ladder characterized by frequent return migration of workers that have left their home region.

Motivated by these facts, in the second part of the paper we develop a framework to study the joint allocation of labor across firms and regions. We design a wage-posting model with heterogeneous firms, multiple regions, worker heterogeneity, and a large set of spatial frictions often considered in the migration literature: moving costs, home bias, spatial search costs, and region-specific comparative advantages. Firms choose the wage to post and decide how many job vacancies to open. Workers decide how many job applications to submit to each region and move into and out of unemployment and across firms both within and between regions. A constant returns to scale matching function transforms applications and vacancies into worker-firm meetings. Search is directed across regions, but random within region, which is important for identification of the spatial frictions.

Our model allows us to identify the different spatial frictions and to isolate them from general labor market frictions. While all model parameters and frictions are jointly identified, we provide a heuristic identification argument.

First, the unobservable distribution of job offers in each region is disciplined by within-region data on the joint distribution of wages and firm size, the average wage gains of job movers, and the frequency of job changes.

Second, given within-region offer distributions, the spatial frictions are identified by comparing the wage gains and job flows across regions to their within-region analogues. Higher observed wage gains for movers into a region compared to movers within that region reflect the presence of moving costs, as cross-region job switchers need to be compensated to move. Similarly, higher wage gains for movers out of their home region relative to other worker types making the same move identify home preferences. In contrast, spatial search costs are disciplined by the relative frequency of job switches. Lower worker flows across regions, compared to between firms within region, indicate that workers are less able to apply for jobs in other regions.

We estimate the model with four sub-regions of Germany corresponding to the Northwest, Southwest, Northeast, and Southeast, which we refer to as *locations* to distinguish them from the regions of East and West Germany. We incorporate four worker types reflecting the four possible home locations.

Our estimates imply large spatial barriers, mainly due to the limited ability of workers to access job opportunities that are further away, consistent with evidence that labor markets are primarily local (e.g., Manning and Petrongolo (2017)). For a given search effort, workers generate 1/20th as many job applications when searching for jobs across locations as within. We estimate a cost of moving between any two locations of 3.1%-5.3% of lifetime income (dependent on the distance of the move), and find that workers need to be paid 7.4% of their yearly income to work away from their home location and maintain the same utility.

We then turn to the main exercise of our paper and use the estimated model to quantify the aggregate and distributional costs of spatial frictions in general equilibrium. Removing all spatial frictions, including workers' home bias, would raise GDP per worker in Germany by almost 5%, and average real wages by 9%. Importantly, these gains are due to improvements in the allocation of labor to firms *within* each location, rather than due to net migration from low to high productivity areas. When spatial frictions are removed, firms are exposed to more competition from other locations, which forces unproductive firms to shrink or to exit and reallocates labor towards high productivity firms in each location. This adjustment in firms' behavior accounts for the majority of the gains we find. Additionally, workers also gain due to better job opportunities as they climb an integrated Germany-wide job ladder.

Our model also sheds light on the distributional effects of spatial frictions. When spatial frictions are removed, East Germany's output per worker rises by 17%, while output in the West increases by only 4%. Similarly, East Germans see their wage rise by almost 20%, while West Germans gain only about 7%. Both the reallocation of labor within and across locations are important for these effects. Removing spatial frictions leads to a greater labor reallocation within East Germany than in the West because the East has more unproductive firms, which are more affected by spatial frictions. Labor reallocation across locations allows East Germans to benefit from the higher wages paid in the West, and increases the average skill level of the East German labor force due to the in-migration of West Germans.

Our results remain qualitatively unchanged when we eliminate only the spatial frictions generated by technological parameters (the moving cost and the spatial search frictions), while keeping workers' preference for their home region. However, we find strong complementarities between these types of frictions: removing technological frictions and home preferences separately generates only half of the gains from removing both sources of frictions at the same time.

In the final part of the paper, we demonstrate that the gains from removing spatial frictions decline sharply as the labor mobility within each location increases. The reason is intuitive: with more within-location mobility, labor is relatively concentrated at the most productive firms, hence the marginal gains from removing spatial frictions, which arise mostly due to better within-location reallocation of labor, are limited. Importantly, we show that the average wage gap between two locations does not depend in general on the level of labor market frictions. Consequently, two economies could look *identical* in terms of their wage or productivity gap between locations, yet removing spatial frictions could lead to vastly different aggregate gains dependent on the economies' local labor market frictions.

Literature. We build on a large body of work that has studied the impact of factor misallocation on aggregate productivity (e.g., Hsieh and Klenow (2009)). In particular, we add to the growing macro literature on the role of labor market frictions in misallocating labor (Lentz and Mortensen (2012); Engbom (2020); Bilal et al. (2022); Bilal (2023); Elsby and Gottfries (2022); Martellini (2022)). Our contribution is to study jointly the allocation of labor across firms and space, and to quantify how spatial frictions shape competition in the local labor market. Our analysis is motivated by recent work showing that workers' job search is mostly local.[2]

Our paper also builds on the quantitative spatial literature that has developed general equilibrium frameworks to study the aggregate and distributional impacts of barriers to the mobility of labor across space, industries, and occupations (e.g., Caliendo et al. (2019); Bryan and Morten (2019); Hsieh et al. (2019)). Our contribution to this literature is to focus on a different margin of misallocation *(across firms of different productivities)* and to show how we can quantify it using a model with labor market frictions and matched employer-employee data.[3] Typically, the quantitative spatial literature allows for rich spatial heterogeneity and

[2] For example, Manning and Petrongolo (2017) and Le Barbanchon et al. (2020).

[3] These type of data have, to the best of our knowledge, not yet been used by this literature. One way to see our contribution is that we bring to the quantitative literature on spatial frictions insights from the large labor literature that has estimated models with on-the-job search in matched employer-employee data,

individual comparative advantages towards regions and/or occupations. Barriers to labor mobility may then lead to worker-firm mismatch and misallocation of talent. This channel has a very limited role in our framework, in which misallocation is instead driven by misallocation of inputs, closer to the wedge approach of Hsieh and Klenow (2009) but generated endogenously by the interaction between labor and spatial frictions.[4]

Methodologically, we extend a wage posting model à la Burdett and Mortensen (1998) to incorporate a spatial structure. Our framework is related to job ladder models with labor mobility across sectors, such as Meghir et al. (2015), Hoffmann and Shi (2016), and Bradley et al. (2017).[5] A limitation of these models for our context is that they do not consider switching costs between sectors, and therefore two workers with the same current value of employment accept the same job offers regardless of their current sector. In our setup, instead, workers' acceptance decisions not only depend on their current value but also on their current location. To apply the existing frameworks to our context, we would need to assume that there is no cost of moving between locations. Our framework is suitable to situations in which workers' current sector or location is a state variable for employment decisions.

At a conceptual level, we contribute to the fast-growing literature on local monopsony power (e.g., Berger et al. (2022)), and in particular to work that links labor market power to spatial frictions such as commuting costs (e.g., Caldwell and Danieli (2023), Datta (2022)). Relative to this work, our paper analyzes how changes to spatial frictions affect monopsony power and endogenously reallocate workers within local labor markets.[6] The reallocation of workers towards higher productivity firms and the exit of unproductive ones in our model is similar in spirit to the within-industry reallocation in international trade when trade barriers are removed (Pavcnik (2002), Melitz (2003)). However, reallocation in our framework comes from competition for workers in the labor market, rather than for customers in the output market.

Finally, there is a large literature that studies the size of spatial frictions and the gains from

e.g., Lise et al. (2016); Bagger and Lentz (2019); Bonhomme et al. (2019).

[4]Krueger and Pischke (1995), Fuchs-Schündeln et al. (2010), Uhlig (2006) and Uhlig (2008), Dauth et al. (2021), Boeri et al. (2021), and Lindenlaub, Oh, and Peters (2022) focus on understanding the large wage and productivity gaps in the specific German context. We do not seek to provide a comprehensive explanation of the East-West gap in Germany. In particular, we estimate the productivity gap between East and West Germany in our model and take it as given.

[5]A large literature has estimated versions of Burdett and Mortensen (1998) (e.g Van Den Berg and Ridder (1998); Burdett and Coles (2003); Burdett et al. (2020); Moser and Engbom (2022)).

[6]Similar to us, Galenianos et al. (2011) and Bachmann et al. (2021) emphasize how firms' monopsony power reduces employment at highly productive firms; however, these papers do not analyze the role played by spatial frictions.

migration either in partial equilibrium (e.g., Kennan and Walker (2011); Baum-Snow and Pavan (2012)) or by estimating reduced-form specifications in panel data.[7] Relative to these papers, we build a general equilibrium framework that provides a structural interpretation to the reduced form evidence and that can be used to study the aggregate impact of spatial frictions. Closest to our work, Schmutz and Sidibé (2018) build a framework with worker mobility within and across locations subject to a rich set of spatial frictions. In that framework, firms' wages and workers' job offer arrival rates are exogenous, and hence the model cannot be used to study how changing spatial frictions affects local wages or labor market tightness. The key finding in our framework is that a substantial share of the costs of spatial frictions can arise precisely because of changes to firms' equilibrium wage and vacancy posting, hence offer arrival rates: spatial frictions allow low-productivity firms to post more vacancies and reduce firms' offered wages due to lower competition.

Road Map. We proceed as follows. Section 2 describes the data, and Section 3 documents facts on the German labor market. Section 4 introduces the model, which we estimate in Section 5. We quantify the aggregate and distributional effects of spatial frictions in Section 6. Section 7 concludes.

2 Data

We use two datasets provided by the German Federal Employment Agency (BA): i) the Establishment History Panel (BHP) and ii) the longitudinal version of the Linked Employer-Employee Dataset (LIAB).

The BHP is a panel containing a 50% random sample of all establishments in Germany with at least one employee liable to social security on June 30th of a given year. The data are based on social security filings and exclude government employees and the self-employed. Each establishment in the BHP is a company's unit operating in a distinct county and industry.[8] For simplicity, we will refer to these units as "firms". For each firm-year pair, the dataset contains information on location, average wages, number of employees, and employee characteristics (education, age, gender).

The LIAB data contain records for more than 1.9 million individuals drawn from the Integrated Employment Biographies (IEB) of the IAB, which cover all individuals that were

[7]See Combes et al. (2008); Roca and Puga (2017); Hicks et al. (2017); Lagakos et al. (2020); and Card et al. (2023).

[8]Since several plants of the same company may operate in the same county and industry, the establishments in the BHP do not always correspond to plants (Hethey-Maier and Schmieder (2013)).

employed subject to social security or received social security benefits. These data are linked to information about the firms at which these individuals work from the BHP. For each individual, the data provide the entire employment history for the period 1993-2014, including unemployment periods as long as the individual received unemployment benefits. Each observation is an employment or unemployment spell, with exact beginning and end dates within a given year.[9] A new spell is recorded each time an individual's employment status changes, for example due to a change in job, wage, or employment status. For individuals that do not change employment status, one spell is recorded for the entire year.

An important variable for our analysis is each worker's county of residence, reported in the LIAB since 1999, which together with the workplace will be used to analyze workers' mobility across space. In contrast to the other variables, which are newly reported at each spell, the location of residence is recorded at the end of each year for employed workers and at the start of an unemployment spell for unemployed workers and then added to all observations of that year or spell. Workers self-report their residence, and can choose which residence to report if they have multiple homes, leading some workers to report very large distances between residence and work location even though they live in a second home closer to work. To deal with the potential measurement error, we will define several alternative measures of migration below.

We use four additional datasets. First, we obtain information on county-level cost of living from the Federal Institute for Building, Urban Affairs, and Spatial Development (BBSR (2009)), which we use to construct real wages.[10] Second, we use annual data from the German Socio-Economic Panel (SOEP) to corroborate some of our main findings. Third, we use data from the NY Fed's Survey of Consumer Expectations (SCE) to provide support for our model mechanisms. Finally, we use information on firms' profits from the ORBIS database for the model's estimation.

Sample Construction. We refer to the period 2009-2014 as our baseline sample. For some empirical specifications that require a longer sample, we use the years 2004 to 2014. We construct real wages for each county using the BBSR's price index, which we deflate forward and backward in time using state-specific GDP deflators from the statistics offices of the German states. We use time-consistent industry codes at the 3-digit WZ93 level provided by the IAB based on the concordance by Eberle et al. (2011). Since wages are only reported to the IAB up to the upper limit for statutory pension insurance contributions,

[9]We use "unemployment spell" for the period in which an individual receives unemployment benefits. After benefit expiration, individuals are not in our data until they are employed again.

[10]The data cover about two thirds of the consumption basket, including housing rents. We provide further information in Appendix A. East Germany has a 7% lower average price level.

the BHP contains an imputed average wage variable which estimates the censored wages based on Card et al. (2013). For the LIAB, no such variable is provided and we replicate the imputation steps ourselves. We use the corrected, real wages for all our analyses. We use full-time workers only, and exclude Berlin, which cannot be unambiguously assigned to East or West since it was divided between the two. We provide additional details on the data in Appendix A.

3 Motivating Facts

We document three sets of facts: (i) there is substantial wage heterogeneity both across regions and across firms within these regions; (ii) workers obtain large wage gains when they change jobs, both across and within regions; (iii) workers' job flows are biased towards their home region and towards geographically closer jobs.

3.1 Wage Heterogeneity Between and Within Regions

Figure 1a shows that there is a large difference in the average real wage paid between counties in East and in West Germany in our baseline period. To examine whether this wage gap is due to observables, we run in the BHP firm-level regressions

$$\log(\bar{w}_{jt}) = \gamma \mathbb{I}_{j,East} + \beta X_{jt} + \delta_t + \epsilon_{jt}, \tag{1}$$

where $\bar{w}_{jt}$ is the average real wage paid by firm j in year t, $\mathbb{I}_{j,East}$ is a dummy for whether firm j is located in the East, X_{jt} is a vector of controls, and δ_t are time fixed effects. We find an East-West wage gap of $\gamma = -.2609$ (s.e. .0074) without controls. Controlling for workers' average education, age, female share, firm size, and industry lowers the real wage gap to $\gamma = -.2052$ (s.e. .0027); about 80% of the gap remains unexplained.

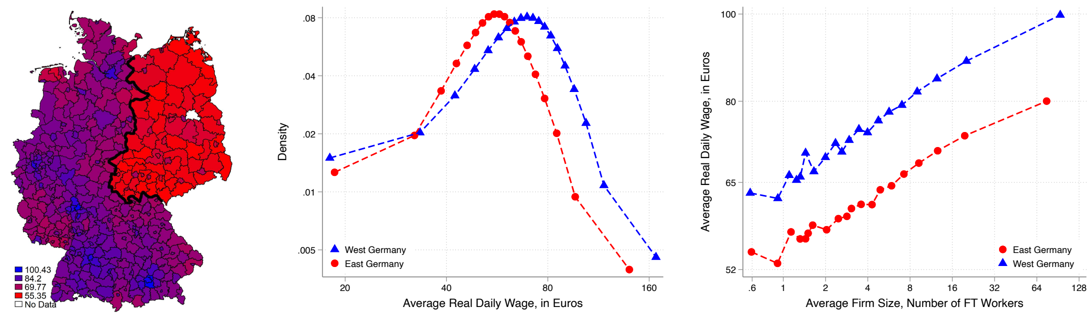
While the wage gap between East and West Germany is striking, we next show that there is even larger wage heterogeneity between firms within each region. Figure 1b plots the real wage distribution in each region (residualized by industry) and shows that the wage gap between the lowest- and highest-paying firms in each region exceeds the average wage gap between East and West.[11]

Figure 1c further plots the average firm size against the firms' average real wage for twentiles of the firm size distribution. Average real wages increase significantly with firm size in both regions, suggesting a job ladder. Additionally, East German firms pay a lower real wage than West German ones for each firm size, suggesting the presence of frictions that shield

[11] In Supplemental Appendix L, available on the authors' websites, we show that there is similarly large wage dispersion across firms even *within the same county*. Hence the large dispersion is not just reflecting cross-county differences, consistent with the limited dispersion shown in Figure 1a.

Figure 1: Real Wages Between and Within Regions

(a) Between Regions (b) Within-Region (c) Wage-Size Ladders



Source: BHP and authors' calculations. Notes: The left figure shows real daily wages in each county in 2009-2014, expressed in 2007 euros valued in Bonn, the former capital of West Germany, and using county-specific prices. Former East-West border is drawn in black for clarification. We exclude Berlin since we cannot assign it unambiguously to "East" or "West". The middle panel plots the density of the average wage of firms in each twentile of the wage distribution. Wages are residualized by regressing the log real wage on 3-digit industry dummies and time dummies, for East and West Germany separately. The cleaned wage is the residuals from this regression plus the mean of the log wage in each region, transformed back into levels. While all firms are weighted equally, only a very small share of overall employment is at the lowest wage firms. The right panel plots the average number of full-time workers for each twentile of the firm size distribution against the average real daily wage of firms in the twentile, where wages and size are residualized as before. The x-axis indicates the average number of workers in each twentile; note that the top twentile includes also a few firms with a very large number of workers, which would thus have a large weight in the calculation of the overall average wage.

East German firms from West German competition and allow them to reach a larger size at the same wage level.

In Supplemental Appendix L[12], we show that the wage gap is accompanied by a large difference in unemployment rates between the two regions. We also provide details of regression (1) and provide additional empirical results: (i) the between-region wage gap is persistent over time and similar for all industries; (ii) there are limited differences in observables between East and West Germans; (iii) there are no clear regional differences in tax rates.

3.2 Large Wage Gains of Movers Across and Within Regions

We show that workers obtain large wage gains when they change jobs, both across and within regions.

We analyze workers' wage dynamics around the time of a job-to-job move by running a standard system of local projections, consisting of one regression for each time period $\tau \in \{t-3, ..., t-1, t+1, ..., t+5\}$ around t:[13]

[12]This Supplemental Appendix is not meant for publication and includes additional material to provide context or robustness checks. It is available on the authors' websites.

[13]We pool together all data for time t from 2004 to 2014, creating an unbalanced panel. Working with an unbalanced panel could be problematic. In our case, we are less concerned because: i) we do not observe post-trends; and ii) we are focused on the wage growth on impact.

$$\Delta \log(w_{i\tau}) = \sum_{s\in\mathbb{S}} \beta^{West}_{s,\tau} d^s_{it}(1 - \mathbb{I}^{East}_i) + \sum_{s\in\mathbb{S}} \beta^{East}_{s,\tau} d^s_{it}\mathbb{I}^{East}_i + B_\tau X_{it} + \epsilon_{it}, \tag{2}$$

where $w_{i\tau}$ is an individual's weighted average wage across all employment spells in year τ, and we use each spell's length as its weight. We define a job-to-job move as a job switch between two firms without intermittent unemployment spell.[14] The variable $\Delta \log(w_{i\tau})$ is the log change of the average wage between year τ and the previous year except for $t+1$, where it is the difference with respect to $t-1$. We drop wages from the year of the move to avoid contaminating our results by other payments.[15]

The variable d^s_{it} is a dummy for a job switch of type $s \in \mathbb{S}$, where $\mathbb{S}$ is the set of the six possible types of moves: i) from East to West via migration or ii) commuting; iii) from West to East via migration or iv) commuting; v) within-East, and vi) within-West. We distinguish between migration and commuting for moves between East and West Germany because we expect that commuters to a new job are paid a smaller wage premium than workers that also have to move their residence. We classify job-to-job movers between East and West Germany as migrants if they report a different county of residence in the year of the move from the previous year, and define all other moves between East and West as commuting.[16]

The variable $\mathbb{I}^{East}_i$ is a dummy for whether an individual's birth region is East Germany. Since our social security data do not contain information on birth location, we classify individuals as East (West) German if at the first time they appear in our entire dataset since 1993, either employed or unemployed, they are in the East (West). Appendix A provides more details. Our measure is imperfect, since some individuals migrated between the reunification and 1993. In Appendix C, we use survey data from the SOEP, which include individuals' actual birth location, to show that our measure properly classifies individuals into the region in which they were born in more than 90% of the cases. For this reason, we will interpret workers' home region also as their birth region going forward, and refer to individuals whose home is East as "East-born".[17]

The controls X_{it} include current work region by home region dummies, distance dummies

[14]Recall that we use "unemployment spell" for the period in which an individual receives unemployment benefits, which we observe.

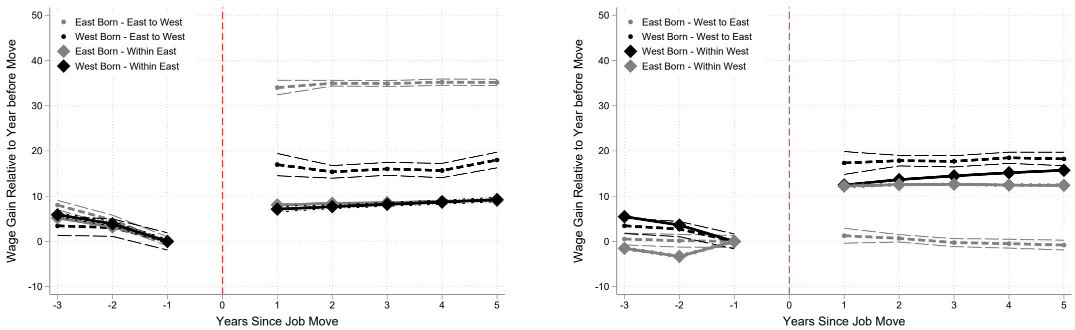
[15]The results are similar if we include year t, see Supplemental Appendix M.

[16]We compare residence location across years since the variable is only updated at the end of each year. As discussed above, the residence variable is subject to measurement error. Our migration measure only includes workers that actively change their recorded residence in the year of the move. We provide several summary statistics on our migration measure in Appendix B.

[17]None of our results hinge on the home region being the birth region, though it does alter the interpretation. An alternative interpretation would be that an individual's location when they first enter the labor market shapes their attachment and biases.

Figure 2: Wage Gains for Job-to-Job Moves

(a) East-to-West Migration vs. Within-East (b) West-to-East Migration vs. Within-West



Source: LIAB and authors' calculations. Notes: The figure is constructed by taking the point estimates for different sets of coefficients $\beta^{West}_{s,\tau}$ and $\beta^{East}_{s,\tau}$ from the regressions (2) for $\tau \in \{t-3, ..., t-1, t+1, t+5\}$. We then sum up the coefficients starting at $\tau = -3$ to obtain for each period τ the sum $\sum_{u=-3}^{\tau} \beta^{i}_{s,u}$, where $i \in \{\text{West, East}\}$, and subtract from this sum the term $\sum_{u=-3}^{-1} \beta^{i}_{s,u}$ to normalize the coefficients with respect to period $\tau = -1$. The dotted lines represent the 95% confidence intervals. The dashed lines in the left panel show the normalized coefficients for $\beta^{West}_{EW,\tau}$ and $\beta^{East}_{EW,\tau}$, and the solid lines with diamonds show $\beta^{East}_{EE,\tau}$ and $\beta^{West}_{EE,\tau}$. The dashed lines in the right panel show the normalized coefficients for $\beta^{West}_{WE,\tau}$ and $\beta^{East}_{WE,\tau}$, and the solid lines with diamonds show $\beta^{West}_{WW,\tau}$ and $\beta^{East}_{WW,\tau}$.

since moves further away could lead to higher wage gains, the total number of past job-to-job switches, age controls, and year fixed effects. Since the left hand side variable is wage growth, any difference across individuals in the wage level would be netted out. Therefore, we do not include individual fixed effects in our main specification. The coefficients $\beta^{West}_{s,\tau}$ and $\beta^{East}_{s,\tau}$ capture the real wage gains from making a job-to-job transition relative to the wage growth obtained by staying at the same firm, which is the omitted category.

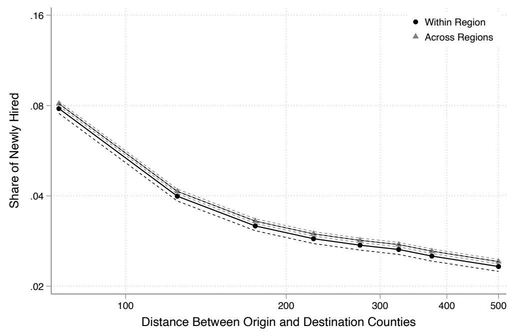
Figure 2a shows that East-born movers to the West receive on average almost a 35% real wage increase relative to their average within-firm wage growth, which is almost double the wage gain obtained by West-born workers making the same move. Figure 2b shows that moves to the East are associated with sizable wage gains for West-born workers and almost no effect for East-born ones. The figures highlight that cross-region movers obtain significant wage increases, in particular those moving out of their home region, suggesting that workers need to be compensated to leave (home bias). Moreover, average wage gains for moves to the East tend to be smaller than for moves to the West, consistent with the lower average wage level in the East, and suggesting the presence of large gains from regional integration.

Workers obtain large wage gains not only from cross-region migration, but also from within-region job switches. Figures 2a and 2b show that workers experience wage gains of on average 10% from within-region job moves, consistent with the notion that they are climbing a job ladder in the presence of labor market frictions.

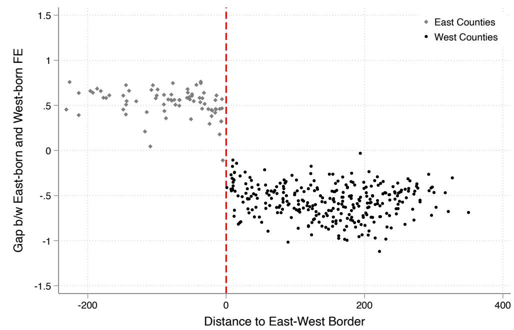
These observational returns from migration and job-to-job moves should not be interpreted

Figure 3: Results from the Gravity Equation: Geography versus Home Bias

(a) Geography



(b) Identity: Destination FE



Source: LIAB. The figures plot results from specification (3). The left panel shows the point estimates for the coefficients for distance, $\hat{\phi}_x$, in black and the distance coefficients for a cross-border move, $\hat{\phi}_x + \hat{\rho}$, in gray, where each coefficient is plotted at the mid-point of the relevant distance interval and the 400+ category is plotted at 500km. All coefficients are transformed into levels by taking their exponent and then normalized into interpretable shares by dividing by their sum plus exp(0) for the omitted category of short-distance moves. Dotted lines represent the 95% confidence interval. The right panel plots the difference between the destination fixed effects for East- and West-born, $\gamma_d^{East} - \gamma_d^{West}$, as a function of the distance of each county d to the East-West border. We normalize the fixed effect coefficients for each worker type by their mean, and plot counties in the East with a negative distance.

as causal effects. Movers are selected: they are the ones that received sufficiently appealing job offers. Nonetheless, these large wage gains highlight the importance of labor mobility, both within and between regions, for aggregate productivity and they will offer relevant empirical targets to which our model is going to provide a structural interpretation.

In Supplemental Appendix M, we list the full estimates from specification (2), and show that the results are broadly similar across demographic groups. We also show robustness to including individual fixed effects and to alternative definitions of job switches and migration.

3.3 Distorted Job Ladder

Finally, we study job flows and show that workers climb a country-wide job ladder, which is distorted by spatial frictions.

Let $n^h_{o,d,t}$ be the number of workers with home region h (either East or West Germany) that were in a job in county o in year $t-1$ and that have made a job-to-job move to a new job in county d in year t. We compute the share $s^h_{o,d}$ of these job-to-job switchers from county o moving to county d (where d can be equal to o) across all years in our core period.[18] We then fit the gravity equation

$$\log s^h_{o,d} = \delta^h_o + \gamma^h_d + \sum_{x \in \mathbb{X}} \phi_x D_{x,o,d} + \rho \mathbb{I}_{R(o) \neq R(d)} + \epsilon^h_{o,d}, \tag{3}$$

[18]We observe at least one job-to-job flow in some year for 75,937 out of the 160,801 possible origin-destination pairs. When we include also job switches with an intermittent unemployment spell – in Supplemental Appendix O – we have 95,275.

Table 1: Summary Statistics on Mobility

		Home: West	Home: East
	Workers moving job-to-job per month...		
(1)	- ... within region	1.13%	1.04%
(2)	- ... across regions	0.01%	0.06%
(3)	Ever crossed border	4.6%	23.9%
(4)	Returned movers	46.3%	36.1%
(5)	Mean years away (returners)	2.90	2.41

Source: LIAB. Notes: The table shows statistics for workers with at least one full-time employment spell in 2009-2014. Row 1 presents the share of these workers moving job-to-job per month within-region, defined as the number of job-to-job switchers whose new job is in the same region as the old one divided by all employed workers in the initial month, and averaged across months. Row 2 presents the average monthly share of movers across regions, defined analogously and taking all job movers across regions. Row 3 shows the share of the workers in our sample that have ever had a full-time job in their non-home region over the entire sample since 1993. Row 4 shows the share of workers that returned to a job in their home region after their first job in the non-home region, and row 5 presents the average number of years away.

where δ_o^h and γ_d^h are county of origin and destination fixed effects, respectively, which differ by workers' home region, $D_{x,o,d}$ are dummies for buckets of distance traveled between origin and destination, and $\mathbb{I}_{R(o)\neq R(d)}$ is a dummy that is equal to one if the job switch is between East and West Germany. The set $\mathbb{X}$ contains seven 50km intervals from 50km-99km onward to 350km-399km and an eighth group for counties that are further than 399 km apart. The term $\mathbb{I}_{R(o)\neq R(d)}$ captures any geographical barriers beyond distance affecting mobility between East and West Germany. The home-region specific fixed effects δ_o^h and γ_d^h capture the fact that some counties may be more attractive to workers of home region h, due to preferences, comparative advantage, or possibly due to a social network that allows them to find job opportunities.

Figure 3a shows that workers move mostly locally, and job switches become less likely for counties that are further apart.[19] Conditional on the origin and destination effects, we do not find a role for geographical barriers at the East-West border, since the gray line (the coefficients $\hat{\phi}_x + \hat{\rho}$) is almost on top of the black one.

Figure 3b shows that East individuals have significantly higher destination fixed effects for counties in East Germany. This result implies that East Germans are more likely to move to counties in the East than West German workers regardless of their current location.[20] Conversely, East-born workers are less likely to move to counties in the West. Supplemental Appendix O shows that the mobility patterns are broadly similar for different demographic sub-groups and for different definitions of migration.

[19] We show the full list of estimated coefficients of regression (3) in Supplemental Appendix O.

[20] In gravity equations, the level of the fixed effects is not identified. We normalize the fixed effects for both East-born and West-born workers relative to their average. This normalization is without loss of generality since we are interested only in the relative fixed effects across counties.

Despite the strong effects of distance and home bias on worker mobility, the labor markets of East and West Germany are, in fact, tightly connected. Table 1 shows that on average 1% of all employed West and East Germans switch jobs within-region in an average month (row 1). For East Germans, the job-to-job transition rate across regions is about one twentieth as high as the transition rate within region (row 2). Row 3 illustrates that 4.6% of West-born and 23.9% of East-born in our sample have ever had a full-time job in the other region over the entire period since 1993. However, between one third and one half of the workers taking a job in the other region return to a job at home, after spending on average only 2-3 years away (rows 4-5).[21] Overall, workers climb a country-wide job ladder, but this ladder is distorted by spatial frictions since workers change jobs mostly locally and frequently return home. The substantial return migration implies that the gains from cross-region migration may be short-lived if workers, when returning home, move to relatively low productivity firms. This possibility highlights the importance of studying worker allocation to firms both within and between regions.

In Appendix B we present additional statistics on movers and show that the share of workers away from their home region has been relatively stable recently. This fact, together with the stable wage gap, motivates our analysis in steady state below.

4 Model

We now develop a model to quantify how spatial barriers and labor market frictions jointly affect worker mobility across space and firms. The model's ingredients are tied to the empirical facts shown above: (i) the wage dispersion and wage gains within-region call for a model with labor market frictions; (ii) the spatial wage gaps and the asymmetries in wage gains and job flows necessitate a model with mobility costs and home bias; (iii) the presence of repeated moves across East and West suggests a framework in which individuals draw (infrequently) jobs from different regions. To capture these facts, our framework embeds the on-the-job search model of Burdett and Mortensen (1998) into a multi-region economy inhabited by heterogeneous firms and workers, subject to different types of spatial frictions commonly used in the literature: moving costs, home preferences, regional comparative advantages, and spatial search frictions.[22]

[21] The average non-returner is employed in the other region, until her employment history ends, for more than three times as long: 9.4 years for West Germans and 7.5 years for East Germans.

[22] We introduce spatial search frictions that make it easier for workers to find jobs locally, building on a recent literature which uses job application data to show that workers' number of applications declines sharply with the distance of the vacancy (Manning and Petrongolo (2017); Le Barbanchon et al. (2020)). Schmutz and Sidibé (2018) also incorporate similar frictions into their *partial equilibrium* model to capture the lack of migration between areas with different unemployment rates. In Bilal (2023), instead, unemployed

Table 2: Economic Environment

Workers of types i	$\bar{D}^i$, θ^i_j
Preferences for each location j	τ^i_j
Workers' indirect utility	$\mathcal{V}^i_j = w\theta^i_j\tau^i_j/P_j$
Moving costs between locations	κ^i_{jx}
Applications and spatial search frictions	$a^i_{jx}\left(s_x\right) = z^i_{jx}s_x$
Application cost (employed and unemployed)	$\psi\left(s_x\right) = \frac{s_x^{1+\epsilon}}{1+\epsilon}$, $\psi_u\left(s_x\right) = \nu^{-\epsilon}\frac{s_x^{1+\epsilon}}{1+\epsilon}$
Extreme value shocks upon an offer	$\left(\varepsilon_j, \varepsilon_x\right) \sim EV\left(0, \sigma\right)$
Firms' distribution within location j	M_j, $p \sim \gamma_j\left(.\right)$
Firm output net of vacancy cost (in steady state)	$vp\sum_{i\in\mathbb{I}}\theta^i_j l^i_j(w) - \xi_j\left(v\right)$
Random matching in each location j	$M\left(\bar{a}_j, \bar{v}_j\right) = \bar{a}_j^{\chi}\bar{v}_j^{1-\chi}$
Law of motion of labor per vacancy	$\dot{l}^i_j\left(w\right) = \vartheta_j^{-\chi}\frac{\bar{a}^i_j}{\bar{a}_j}\mathcal{P}^i_j\left(w\right) - q^i_j\left(w\right)l^i_j\left(w\right)$
Relative local price	$\frac{P_j}{P_x} = \left(\frac{P_jY_j}{P_xY_x}\right)^{\alpha(1-\eta)}\left(\frac{K_j}{K_x}\right)^{-\alpha(1-\eta)}$

We solve the model in general equilibrium to study the effects of removing spatial barriers on the allocation of workers to firms. The model is dynamic, but we focus on the tractable stationary equilibrium since the East to West wage gap is persistent and the number of workers away from home has been stable in recent years.

4.1 Environment

Let time be continuous and all agents discount future income at rate r. We consider an economy partitioned into $\mathbb{J} = \{1, ..., J\}$ sites, which we refer to as *locations*.[23] Table 2 shows the key features of the environment, which we now describe.

Workers. There is a continuum of workers of types $i \in \mathbb{I}\{1, .., I\}$ with mass $\bar{D}^i$, where $\sum_{i\in\mathbb{I}}\bar{D}^i = 1$. Throughout the text, we will use superscripts for worker types and subscripts for locations. Workers of type i have a preference parameter τ^i_j for being at location j, and consume both a tradable and a local good, such as housing. Their utility is $\mathcal{U}^i_j = \tau^i_j c^\eta h^{1-\eta}$, where c and h are the amounts of tradable good and local good, respectively. A worker of type i produces θ^i_j units of output per time unit in location j. Her indirect utility from receiving wage rate w in location j is $\mathcal{V}^i_j = w\theta^i_j\tau^i_j/P_j$, where $P_j = \left(P_c\right)^\eta\left(P_{h,j}\right)^{1-\eta}$ is the location's price level, P_c is the price of the tradable good, and $P_{h,j}$ the price of the local good.[24] We normalize $P_c = 1$.

Workers choose search effort s_x for each location x, file applications, and randomly and

workers search for jobs only in their local market.

[23]We introduce the term "locations" to differentiate it from the two regions in the empirical section. We will estimate the model below with four locations: two in the East and two in the West.

[24]We omit the constant in the indirect utility.

infrequently receive wage offers from firms. Search effort s_x directed by worker i in location j to location x generates $a_{jx}^{i}\left(s_x\right) = z_{jx}^{i} s_x$ job applications, where z_{jx}^{i} is the worker's search efficiency. Search effort is subject to a cost, to be paid separately for each location x in which the worker files applications, given by $\psi\left(s_x\right) = \frac{s_x^{1+\epsilon}}{1+\epsilon}$ for employed workers and $\psi_u\left(s_x\right) = \nu^{-\epsilon}\frac{s_x^{1+\epsilon}}{1+\epsilon}$ for unemployed ones. Here, $\nu \geq 1$ modulates the higher search intensity of unemployed workers along the lines of Moscarini and Postel-Vinay (2016). Upon receiving an offer from location x, workers draw idiosyncratic preference shocks for current location j (ε_j) and destination location x (ε_x) from a type-I extreme value distribution with zero mean and standard deviation σ.[25] We assume that workers can always separate into unemployment keeping the same shocks, which allows us to pin down the lower bound for wages in each location, as in the original formulation of Burdett and Mortensen (1998). Movers between j and x incur a utility cost κ_{jx}^{i} that captures any monetary and non-monetary one-time cost associated with the move across locations.[26]

Workers accept an offer if it provides higher value than the current one, solving

$$\max\left\{W_j^i\left(w\right) + \varepsilon_j; W_x^i\left(w'\right) - \kappa_{jx}^i + \varepsilon_x\right\},$$

where $W_j^i(w)$ and $W_x^i(w')$ are the values of employment at wage w and w' in locations j and x, respectively, and $\kappa_{jx}^i = 0$ if $j = x$. The value $W_j^i(w)$ solves

$$\begin{aligned} rW_j^i\left(w\right) &= \frac{w\theta_j^i\tau_j^i}{P_j} + \delta_j^i\left[U_j^i - W_j^i\left(w\right)\right] \\ &+ \max_{\{s_x\}_{x\in\mathbb{J}}}\sum_{x\in\mathbb{J}}\left(a_{jx}^i\left(s_x\right)\vartheta_x^{1-\chi}\left[\int V_{jx}^{E,i}\left(w,w'\right)dF_x\left(w'\right) - W_j^i(w)\right] - \psi\left(s_x\right)\right). \end{aligned} \tag{4}$$

The first term, $w\theta_j^i\tau_j^i/P_j$, is the real flow value of employment. The second term is the continuation value for separating into unemployment, which occurs at rate δ_j^i. The third term is the continuation value for drawing new job offers from all the locations x, where $V_{jx}^{E,i}\left(w,w'\right) \equiv \sigma\log\left(\exp\left(W_j^i\left(w\right)\right)^{\frac{1}{\sigma}} + \exp\left(W_x^i\left(w'\right) - \kappa_{jx}^i\right)^{\frac{1}{\sigma}}\right)$ due to properties of the the type-I extreme value distribution. Applications become jobs at the equilibrium rate $\vartheta_x^{1-\chi}$. Last, $\left\{F_j\right\}_{j\in\mathbb{J}}$ are the endogenous distributions of wage offers in each region, generated by the firm's problem as we describe below.

[25] These are shocks to workers' preferences for being in a specific firm and location. The problem is isomorphic to an alternative formulation in which workers only draw a shock for the value of accepting the offer, where that shock follows a logistic distribution.

[26] We do not allow workers to move across locations without a job, i.e., into unemployment. This choice is driven by the fact that our data do not allow us to observe this specific type of move. As described above, unemployed workers' residence location is recorded only at the beginning of an unemployment spell but not subsequently, and most unemployed workers file for unemployment benefits at the location of their last job.

Unemployed workers receive a benefit rate b_j^i and their value thus solves

$$rU_j^i = \frac{b_j^i \theta_j^i \tau_j^i}{P_j} + \max_{\{s_x\}_{x\in\mathbb{J}}} \sum_{x\in\mathbb{J}} \left(a_{jx}^i (s_x) \vartheta_x^{1-\chi} \left[\int V_{jx}^{U,i} \left(b_j^i, w'\right) dF_x(w') - U_j^i \right] - \psi_u(s_x) \right), \tag{5}$$

where $V_{jx}^{U,i}\left(b_j^i, w'\right) \equiv \sigma \log \left(\exp\left(U_j^i\right)^{\frac{1}{\sigma}} + \exp\left(W_x^i(w') - \kappa_{jx}^i\right)^{\frac{1}{\sigma}} \right)$.

Firms and Goods Market. In each location $j \in \mathbb{J}$ there is a mass M_j of firms, with $\sum_{j\in\mathbb{J}} M_j = 1$. Firms are distributed over productivity p with location-specific density $\frac{\gamma_j(p)}{M_j}$ with support on a closed set $[\underline{p}_j, \bar{p}_j] \subseteq \mathbb{R}^+$.[27] Firms cannot change location.[28]

Each firm decides how many vacancies $v_j(p)$ to post (including zero) and what wage rate $w_j(p)$ to offer, which jointly determines firm size, and then allocates labor to the production of the tradable and the local good. Denote by l_j^i the measure of workers of type i employed per vacancy of a firm, so that $n_j \equiv \sum_{i\in\mathbb{I}} \theta_j^i l_j^i$ is the total measure of efficiency units of labor used by one vacancy. Vacancies can produce any combination of the two goods according to the production functions $c = pn_c$ and $h = (pn_h)^{1-\alpha} k^\alpha$, where $0 < \alpha(1-\eta) < 1$, and n_c and n_h must satisfy $n_c + n_h = \sum_{i\in\mathbb{I}} \theta_j^i l_j^i$. The term k is a factor in fixed supply, such as land, with aggregate supply in location j of K_j and equilibrium price ρ_j.

We first take as given the measure of workers hired and solve the firm's problem of allocating workers between the two goods. A firm that has hired n_j units of labor per vacancy maximizes profits excluding labor costs:

$$\hat{\pi}_j(n_j) = \max_{n_h, n_c, k} \left\{ pn_c + P_{h,j} (pn_h)^{1-\alpha} k^\alpha - \rho_j k \right\} \tag{6}$$

subject to $n_c + n_h = n_j$. Standard optimization and market clearing conditions imply that in equilibrium the relative price between any two locations j and x satisfies

$$\frac{P_j}{P_x} = \left(\frac{P_j Y_j}{P_x Y_x}\right)^{\alpha(1-\eta)} \left(\frac{K_j}{K_x}\right)^{-\alpha(1-\eta)}, \tag{7}$$

where $P_j Y_j$ is the nominal output of location j, and recall that $P_{h,j}^{1-\eta} = P_j$.[29] Substituting

[27] Thus, $\gamma_j(p)$ will integrate to the mass of firms in location j, M_j.

[28] This assumption is motivated by the fact that our data is at the establishment level and does not contain firm identifiers, and thus we cannot see firms relocating or deciding where to open establishments. The model, nonetheless, could easily be adapted to allow entrepreneurs to make a location choice. As described further below, we allow firms to change their size by changing their number of vacancies, and to effectively enter or exit (across steady states) by going from zero to positive vacancies or vice versa.

[29] If more labor moves to location j, increasing output Y_j relative to Y_x, then the relative local price index P_j/P_x rises, due to the presence of the fixed factor. As a result, there is local congestion as typical in spatial

in the optimal choices and equilibrium price, we can simplify $\hat{\pi}_j(n_j)$ to

$$\hat{\pi}_j(n_j) = pn_j = p\left[\sum_{i\in\mathbb{I}} \theta_j^i l_j^i(w)\right]. \tag{8}$$

The firm's profits thus become a linear expression in n_j, as in the standard Burdett-Mortensen framework. We provide details in Appendix D.1.

We now turn to the firm's wage posting problem. Since the firms' production functions are linear, the firm-level problem of posting vacancies and choosing wages can be solved separately. Total profits per vacancy are $\pi_j(n_j) = \max_w \{\hat{\pi}_j(n_j) - wn_j\}$. Using (8), the wage rate maximizes

$$\pi_j(p) = \max_w (p - w)\left[\sum_{i\in\mathbb{I}} \theta_j^i l_j^i(w)\right]. \tag{9}$$

In choosing which wage to offer, firms take into account that a higher wage reduces their profit margin, but allows them to hire and retain more workers since, as we discuss below, the equilibrium function $l_j^i(w)$ is increasing in w. We assume that firms are competing for all worker types in one unified labor market, hence they must offer only one wage per efficiency unit to all workers.[30]

The number of vacancies per firm then maximizes total profits

$$\varrho_j(p) = \max_v \pi_j(p)\, \vartheta_j^{-\chi} v - \xi_j(v), \tag{10}$$

where $\xi_j(v)$ is a vacancy posting cost. The size of a firm p in location j is thus given by $l_j(w_j(p))v_j(p)$, where $w_j(p)$ is the profit-maximizing wage. A firm of productivity p posts a positive mass of vacancies as long as its profits per vacancy, $\pi_j(p)$, are positive. We define φ_j to be the lowest produtivity firm that posts vacancies in location j, such that $v_j(p) = 0$ for all $p \in [\underline{p}_j, \varphi_j)$.

Matches. Matches in location j are created as a function of the total mass of applications filed by workers of all types i towards j, $\bar{a}_j = \sum_{i\in\mathbb{I}} \bar{a}_j^i$, and vacancies posted by firms, $\bar{v}_j$. Matching takes place according to a matching function $M(\bar{a}_j, \bar{v}_j) = \bar{a}_j^{\chi} \bar{v}_j^{1-\chi}$ as in Diamond-

models (e.g. Allen and Arkolakis (2014)).

[30] This seems an adequate description of the German labor market since we will define worker types based on their home region below, and German law prohibits firms from discriminating against workers based on origin, e.g., East Germans. Previous work with heterogeneous types (e.g. Moser and Engbom (2022)) assumes that the labor market is segmented by type. In our framework, the composition of the worker types a firm attracts, $\theta_j(w) \equiv \left[\sum_{i\in\mathbb{I}} \theta_j^i l_j^i(w)\right] / \left[\sum_{i\in\mathbb{I}} l_j^i(w)\right]$, is endogeneous. While a firms' workers all receive the same wage rate w, their take-home pay $\theta_j^i w$ is increasing in ability.

Mortensen-Pissarides models (e.g., Pissarides (2000)), where

$$\bar{a}_j^i = \sum_{x\in\mathbb{J}} \left[\int a_{xj}^{E,i}(w)\, dE_x^i(w) + a_{xj}^{U,i}(b)\, u_x^i \right], \tag{11}$$

$$\bar{v}_j = \int_{\underline{p}_j}^{\bar{p}_j} v_j(p)\, \gamma_j(p)\, dp. \tag{12}$$

Here, $a_{xj}^{E,i}(w)$ and $a_{xj}^{U,i}(b)$ are the equilibrium measures of applications sent by employed and unemployed workers of type i from x to j, and $E_j^i(w)$ is the mass of employed workers of type i at firms in location j receiving at most w. The matching function implies market tightness in location j of $\vartheta_j \equiv \frac{\bar{v}_j}{\bar{a}_j}$. The rate at which a vacancy is filled is $\vartheta_j^{-\chi}$, and the rate at which an application becomes a job is $\vartheta_j^{1-\chi}$.

Workers can direct applications towards each location, but search is random within location. Therefore, offers in location j are drawn from the following wage distribution

$$F_j(w) = \frac{1}{\bar{v}_j} \int_{\underline{p}_j}^{\hat{p}_j(w)} v_j(p)\, \gamma_j(p)\, dp, \tag{13}$$

where $\hat{p}_j(w) \equiv w_j^{-1}(w)$ is the productivity of the firm paying wage w. This inverse of the wage function exists since the wage function within a given location is strictly increasing as in the standard framework.

Labor Market Clearing. The law of motion for $l_j^i(w)$ is

$$\dot{l}_j^i(w) = \vartheta_j^{-\chi} \frac{\bar{a}_j^i}{\bar{a}_j} \mathcal{P}_j^i(w) - q_j^i(w)\, l_j^i(w) \qquad \text{if} \quad w \geq R_j^i, \tag{14}$$

where $l_j^i(w) = 0$ if $w < R_j^i$, and R_j^i is the reservation wage which solves $rW_j^i\left(R_j^i\right) = rU_j^i$. The first term in (14) is the hiring rate, which consists of the product of three endogenous terms: i) $\vartheta_j^{-\chi}$, the arrival rate of workers for vacancies posted in location j; ii) $\frac{\bar{a}_j^i}{\bar{a}_j}$, the share of applications going towards location j filed by workers of type i; and iii) $\mathcal{P}_j^i(w) \in [0,1]$, the probability that an offer w in location j is accepted by workers of type i. Since there is random matching within location, the acceptance probability is a weighted average of the acceptance probabilities of workers of type i,

$$\mathcal{P}_j^i(w) \equiv \frac{1}{\bar{a}_j^i}\sum_{x\in\mathbb{J}}\left[\int a_{xj}^{E,i}(w')\,\mu_{xj}^{E,i}(w',w)\,dE_x^i(w') + a_{xj}^{U,i}(b)\,\mu_{xj}^{U,i}(b,w)\,u_x^i\right], \tag{15}$$

where $\mu_{xj}^{E,i}(w',w)$ is the probability that an offer w is accepted by an individual currently employed in region x at wage w' and $\mu_{xj}^{U,i}(b,w)$ is the corresponding probability for an unemployed. Their closed form expressions are in Appendix D.2.

The second term in (14) is the separation rate

$$q_j^i(w) \equiv \delta_j^i + \sum_{x\in\mathbb{J}}\vartheta_x^{1-\chi}a_{jx}^{E,i}(w)\int\mu_{jx}^{E,i}(w,w')\,dF_x(w'), \tag{16}$$

which consists of the exogenous separation rate into unemployment plus the rate at which workers receive and accept offers from other firms. As usual, we can use the law of motion (14) to solve for the steady state mass of workers per vacancy (which is zero if $w < R_j^i$)

$$l_j^i(w) = \frac{\mathcal{P}_j^i(w)\,\vartheta_j^{-\chi}\frac{\bar{a}_j^i}{\bar{a}_j}}{q_j^i(w)} \qquad \text{if } w \geq R_j^i. \tag{17}$$

The mass of employed workers i in location j at firms paying at most w satisfies

$$E_j^i(w) = \int_{\underline{p}_j}^{\hat{p}_j(w)} l_j^i(w_j(p))\,v_j(p)\,\gamma_j(p)\,dp. \tag{18}$$

The law of motion for unemployed workers is $\dot{u}_j^i = \delta_j^i e_j^i - \lambda_j^i u_j^i$, where $e_j^i \equiv E_j^i(w(\bar{p}_j))$ and u_j^i are the mass of employed and unemployed workers of type i in location j, respectively, and $\lambda_j^i \equiv \sum_{x\in\mathbb{J}}\vartheta_x^{1-\chi}a_{jx}^{U,i}(b)\int\mu_{jx}^{U,i}(b,w')\,dF_x(w')$ is the rate at which workers leave unemployment. Thus, in steady state, the mass of unemployed workers is

$$u_j^i = \frac{\delta_j^i}{\lambda_j^i + \delta_j^i}\bar{D}_j^i, \tag{19}$$

where $\bar{D}_j^i = e_j^i + u_j^i$ is the total mass of workers i in region j.

4.2 Stationary Equilibrium

As discussed, we focus on the stationary equilibrium, which we now define.

Definition 1: Stationary Labor Market Equilibrium. *A stationary equilibrium consists of a set of search efforts* $\left\{s_{jx}^{E,i}(w), s_{jx}^{U,i}(b)\right\}_{j\in\mathbb{J},x\in\mathbb{J},i\in\mathbb{I}}$*, acceptance probabilities* $\left\{\mu_{jx}^{E,i}(w,w'),\right.$ $\left.\mu_{jx}^{U,i}(b,w')\right\}_{j\in\mathbb{J},x\in\mathbb{J},i\in\mathbb{I}}$*, wage and vacancy posting policies* $\{w_j(p), v_j(p)\}_{j\in\mathbb{J}}$*, wage offer distributions* $\{F_j(w)\}_{j\in\mathbb{J}}$*, labor per vacancy* $\left\{l_j^i(w)\right\}_{j\in\mathbb{J},i\in\mathbb{I}}$*, unemployment* $\left\{u_j^i\right\}_{j\in\mathbb{J},i\in\mathbb{I}}$*, and market tightness* $\{\vartheta_j\}_{j\in\mathbb{J}}$ *such that*

1. *workers file applications and accept offers to maximize their values taking as given tightness* $\{\vartheta_j\}_{j\in\mathbb{J}}$ *and the wage offer distributions,* $\{F_j(w)\}_{j\in\mathbb{J}}$*;*

2. *firms set wages to maximize per vacancy profits, and choose vacancies to maximize overall profits, taking as given the function* $\left\{l_j^i(w)\right\}_{j\in\mathbb{J},i\in\mathbb{I}}$*;*

3. *arrival rates of offers and wage distributions are consistent with wage policies, applications, and vacancy posting, according to (9), (11), and (12);*

4. *firm sizes and worker distributions satisfy (17), (18), and (19).*

The following proposition shows that the wage policies follow a system of differential equations, facilitating the computation of the model.

Proposition 1. *Defining* $\tilde{x}(p) \equiv x(w(p))$ *for any* x*, the* J *location-specific equilibrium wage functions* $\{w_j(p)\}_{j\in\mathbb{J}}$ *solve*

$$w_j(p) \quad = \quad w_j(\varphi_j) + \int_{\varphi_j}^{p} \left((z - w_j(z)) \frac{\left(\sum_{i\in\mathbb{I}} \theta_j^i \frac{\frac{\partial \tilde{\mathcal{P}}_j^i(z)}{\partial z}\tilde{q}_j^i(z) - \tilde{\mathcal{P}}_j^i(z)\frac{\partial \tilde{q}_j^i(z)}{\partial z}}{\tilde{q}_j^i(z)^2} \vartheta_j^{-\chi} \frac{\bar{a}_j^i}{\bar{a}_j}\right)}{\left(\sum_{i\in\mathbb{I}} \theta_j^i \frac{\tilde{\mathcal{P}}_j^i(z)}{\tilde{q}_j^i(z)} \vartheta_j^{-\chi} \frac{\bar{a}_j^i}{\bar{a}_j}\right)} \right) \gamma_j(z)\, dz,$$

together with J *boundary conditions for* $w_j(\varphi_j)$ *satisfying*

$$w_j(\varphi_j) \quad = \quad \max\left\{\min_{i\in\mathbb{I}} R_j^i, \arg\max_{\hat{w}} (\varphi_j - \hat{w}) \sum_{i\in\mathbb{I}} \theta_j^i l_j^i(\hat{w})\right\}.$$

The lowest productivity firm which posts positive vacancies, φ_j*, solves*

$$\varphi_j = \max\left\{\underline{p}_j, \min_{i\in\mathbb{I}} R_j^i\right\}.$$

Proof. See Appendix D.3. □

In Supplemental Appendix P, we show that our model collapses to the Mortensen (2005) framework if we shut down the spatial heterogeneity and the preference shocks.

4.3 Spatial Frictions, Labor Productivity, and Misallocation

We build some intuition for the mechanisms through which spatial frictions affect our main objects of interest, labor productivity (i.e. output per worker) and labor misallocation, before turning to a quantitative estimation of the model in Section 5.

Labor Productivity. Aggregate output per worker, Y, can be written as a weighted average of each location's output per worker using the location's employment share as weight:

$$Y = \sum_{j \in \mathbb{J}} \left(\frac{\bar{e}_j}{\bar{e}} \right) Y_j, \tag{20}$$

where $Y_j = \frac{1}{\bar{e}_j} \int p \sum_{i \in \mathbb{I}} \theta_j^i l_j^i \left(p\right) v_j \left(p\right) \gamma_j \left(p\right) dp$ is local labor productivity, $\bar{e}_j = \sum_{i \in \mathbb{I}} e_j^i$ is the mass of workers in j, and $\bar{e} = \sum_{j \in \mathbb{J}} \bar{e}_j$. Equation (20) shows that labor productivity is shaped by two forces: i) workers' allocation *across locations*, captured by the share of workers in j, $\bar{e}_j/\bar{e}$; and ii) local output per worker Y_j, which is shaped by local productivity and workers' allocation *across firms* in j. We next discuss how spatial frictions affect these two terms.

Worker Allocation across Locations. The mass of workers in location j is:

$$\bar{e}_j \quad = \quad \underbrace{\bar{a}_j^{\chi}}_{\text{Applications}} \; \underbrace{\bar{v}_j^{1-\chi}}_{\text{Vacancies}} \left(\sum_{i \in \mathbb{I}} \underbrace{\left(\frac{\bar{a}_j^i}{\bar{a}_j} \right)}_{\text{Workers' Weight}} \int_{\varphi_j}^{\bar{p}_j} \underbrace{\left(\frac{\tilde{\mathcal{P}}_j^i \left(p\right)}{\tilde{q}_j^i \left(p\right)} \right)}_{\text{Job Appeal}} \underbrace{\frac{v_j \left(p\right) \gamma_j \left(p\right)}{\bar{v}_j}}_{\text{Firm Weight}} dp \right). \tag{21}$$

The first two terms in equation (21) show that employment in location j increases in the mass of applications directed towards the location, $\bar{a}_j$, and vacancies posted there by firms, $\bar{v}_j$. The third term, in parentheses, shows that employment in location j increases in the location's job appeal, as measured by the ratio of the job offer acceptance probability $\tilde{\mathcal{P}}_j^i \left(p\right)$ and the separation rate $\tilde{q}_j^i \left(p\right)$. The average appeal of jobs in location j is a weighted average across firms and workers' applications: more productive firms are more appealing since they offer higher wage, and workers send more applications to locations that are more easily accessible and that have better job opportunities for them.

Spatial frictions affect (and possibly distort) the allocation of labor across locations through all three terms. First, lower search frictions or mobility costs towards a location raise the mass of applications directed to it. Greater preferences for a location have a similar effect. Second, firms post more vacancies when spatial frictions for a location are lower, as workers are easier to attract. Third, the effect on average job appeal is ambiguous: lower spatial frictions allow firms easier access to workers in other locations, including the unemployed, which has a positive effect on the job filling probability $\tilde{\mathcal{P}}_j(p)$. But lower spatial frictions also expose firms to greater competition, which lowers $\tilde{\mathcal{P}}_j(p)$ and raises $\tilde{q}_j(p)$.

Location Productivity and Worker Allocation across Firms. Local output per worker is

$$Y_j = \underbrace{\bar{\theta}_j}_{\text{Workers } \theta} \underbrace{\Gamma_j}_{\text{Firms } p} \left(1 + \int_{\varphi_j}^{\bar{p}_j} \underbrace{\left(\frac{p}{\Gamma_j} - 1 \right)}_{\text{Rel Firm } p} \underbrace{\left(\frac{\sum_{i \in \mathbb{I}} \theta_j^i l_j^i (w_j(p)) v_j(p) \gamma_j(p)}{\bar{\theta}_j \bar{e}_j} - 1 \right)}_{\text{Relative Firm Size}} dp \right). \tag{22}$$

The first two terms of equation (22) show that local output per worker increases in the average skills of the individuals, $\bar{\theta}_j \equiv \frac{1}{\bar{e}_j} \sum_{i \in \mathbb{I}} \theta_j^i e_j^i$, and in the average firm productivity $\Gamma_j = \int_{\varphi_j}^{\bar{p}_j} p dp$. The third term, in parentheses, is a covariance component which measures how labor is allocated to firms. It is larger the more highly skilled workers are allocated to highly productive firms.

Spatial frictions affect each term. First, by affecting the allocation of workers across space, spatial frictions change the average skill of workers in each location.

Second, lower spatial frictions tend to increase average productivity, Γ_j. To clarify the mechanism, consider an economy with only one type of worker and two locations, j and x, that are symmetric except that firms in x are on average more productive. Assume that initially there are insurmountable frictions – e.g., $z_{jx} = z_{xj} = 0$ – so that workers only work in their home location.[31] Consider the impact on location j of increasing z_{jx} and z_{xj}. The lower search frictions raise the continuation value of workers in location j, since they are now able to also search in the higher productivity location x. As long as $\nu > 1$ – i.e., unemployed workers have lower search costs than employed ones – the greater option value of search raises the reservation wage in location j. This rise in the reservation wage increases the lower bound on productivity φ_j, as firms with optimal wages below the new reservation wage are no longer able to attract workers. These firms stop posting vacancies, thus effectively exit, which raises average productivity Γ_j.

Third, lower spatial frictions also affect the covariance term. As seen from the previous example, reducing spatial frictions increases the reservation wage, squeezing the profit margins of all firms in location j. This profit-squeeze is particularly strong for low productivity firms, thus reallocating labor towards higher productivity firms in location j.[32] At the same time,

[31] Note that the reservation wage is lower in location j due to the lower average productivity of firms there (all else equal).

[32] This mechanism has been extensively studied in the context of an increase in minimum wage (e.g. Moser and Engbom (2022)).

there are other, possibly counteracting, mechanisms at play. Firms in location j now have access to a larger pool of unemployed workers, and this effect is particularly relevant for low productivity firms, allowing them to grow relatively more. Additionally, firms in j now face additional competition for workers from location x, and the impact on worker allocation depends on the shape of the equilibrium distribution in x. Finally, if the improvement in the search technology increases the total mass of applications directed to location j, then all else equal labor market tightness rises, leading to a quicker job ladder concentrating labor towards the top of the firm distribution.

Given the competing forces, the overall impact of spatial frictions is a quantitative question. We next turn to the model estimation to quantify the different effects.

5 Bringing the Model to the Data

We bring the model to our German data and quantify the different spatial and labor market frictions that limit the ability of workers to reallocate across firms and regions.

5.1 Estimation

To estimate the model, we impose a few assumptions to reduce dimensionality, calibrate outside of the model all the parameters that have a corresponding empirical moment, and jointly estimate the remaining ones within the structure of the model.

Parametrization and Functional Forms. To keep the estimation time feasible, we set the number of locations to four, two in the West and two in the East $-$ Northwest ($j = NW$), Southwest ($j = SW$), Northeast ($j = NE$), and Southeast ($j = SE$), and choose four worker types, which are distinguished by their home location.[33] We can thus distinguish the role of the former East-West border from other spatial frictions between locations, and we will continue to refer to East and West Germany overall as "regions". Parametrization with four locations implies that we need to match $4 \times 4 \times 4 = 64$ wage gains and 64 worker flows. We show in robustness below that increasing the number of locations to 24 (12 in the East and 12 in the West) does not substantially alter our results.

We set a unit interval of time to be one month.[34] Firms' log productivity is drawn from a log-normal distribution with equal variance in all locations, Σ, and mean A_j, normalized with $A_{NW} = 1$. We assume in the baseline that all firms post positive vacancies since we

[33] Appendix A provides details on the locations.

[34] For example, we measure empirically the average probability that a worker moves into unemployment during a month, call it $Prob_u$, and then – since the model is in continuous time – we can recover the Poisson rate δ at which unemployment shocks arrive as $Prob_u = 1 - e^{-\delta}$.

do not observe firms that do not enter, and thus $\varphi_j = \underline{p}_j$.[35] The vacancy cost function is $\xi_j(v) = \xi_{0,j} v^{1+\xi_1} \bar{\pi}_j(p)$, where the curvature ξ_1 is constant across locations but $\xi_{0,j}$ is specific to the overall region – i.e. we estimate $\xi_{0,W}$ and $\xi_{0,E}$.

We pin down the unemployment benefits b_j^i by setting the reservation wages R_j^i to be a fraction ι of the lowest firm productivity, $R_j^i = \iota \underline{p}_j$, with ι to be estimated. While R_j is endogenous, setting its value directly is the same as choosing a set of unemployment benefits b_j^i that solve $U_j^i = W_j^i(R_j)$.

We restrict the different sources of spatial frictions – τ_j^i, κ_{jx}^i, and z_{jx}^i – as follows

$$\begin{aligned}
\tau_j^i &= \tau_j \left(1 - \tau_l \mathbb{I}_{(i \neq j) \cap (r(i) = r(j))}\right) \left(1 - \tau_r \mathbb{I}_{r(i) \neq r(j)}\right) \\
\kappa_{jx}^i &= \begin{cases} 0 & \text{if } j = x \\ \kappa_0 e^{\kappa_1 dist_{jx}} \bar{W}^i & \text{if } j \neq x \end{cases} \\
z_{jx}^i &= \begin{cases} \left(1 - z_{l,1} \mathbb{I}_{i \neq j}\right) & \text{if } j = x \\ \left(z_0 e^{-z_1 dist_{jx}}\right) \left(1 + z_{l,2} \mathbb{I}_{i = x}\right) \left(1 + z_r \mathbb{I}_{(r(i) = r(x)) \cap (i \neq x)}\right) & \text{if } j \neq x \end{cases} .
\end{aligned}$$

Preferences τ_j^i are the product of general amenities of location j (τ_j), the worker's utility cost to live outside of her home location but inside her home region (τ_l), and the cost to live outside the home region (τ_r). The index function $r(i)$ maps location i to its region. The moving cost κ_{jx}^i is symmetric (which is important for identification, as we discuss below) and proportional to the average value for each worker, $\bar{W}^i \equiv \frac{1}{\bar{e}^i} \sum_{j \in \mathbb{J}} \int W_j^i(w) \, dE_j^i(w)$, where $\bar{e}^i \equiv \sum_{j \in \mathbb{J}} E_j^i(w(\bar{p}_j))$. The search efficiency is a function of whether the worker searches within the current location ($z_{l,1}$), of the distance of the destination location (z_0,z_1), and of whether the search is directed towards the home location or region ($z_{l,2}$, z_r).

Calibrated Parameters. We calibrate eight sets of parameters listed in Table 3. We describe how we set their values in Appendix E, and focus here on how we set workers' relative productivity, θ_j^i (row 1). Due to wage posting and since firms post the same wage to all workers, the model yields a log additive wage equation

$$\log w_j^i(p) = \log \theta_j^i + \log w_j(p) .$$

This equation is similar to the specification by Abowd et al. (1999), with the main difference that in our specification θ_j^i is both individual- and location-specific. This allows for *comparative advantage*, i.e., a worker employed in her home location could have higher productivity

[35] In the counterfactuals, we solve for φ_j in equilibrium, hence allow firms to post zero vacancies, i.e., exit.

Table 3: Calibrated Parameters

	Parameters	Source		Values: West	Values: East
(1)	θ^i: Workers' skills	AKM in LIAB, see Appendix E	*North*	1	0.911
			South	0.986	0.896
(2)	M_j: Firms by location	BHP	*North*	0.377	0.088
			South	0.445	0.090
(3)	$\bar{D}^i$: Workers by home location	Growth accounting of the States (VGRdL)	*North*	0.362	0.118
			South	0.400	0.120
(4)	δ_j: Separation rate by location	Separation rate from LIAB	*North*	0.011	0.017
			South	0.012	0.015
(5)	P_j: Price Level by location	Price levels from BBSR	*North*	1	0.948
			South	1.029	0.941
(6)	$\alpha(1-\eta)$: Payments to fixed factors	Valentinyi and Herrendorf (2008)		0.05	
(7)	χ: Elasticity of matching function	Assumption		0.50	
(8)	r: Monthly interest rate	Assumption		0.5 %	

Notes: This table reports all the parameters that are calibrated outside of the model before the estimation is run. The "Source" column provides the data source.

there. We show in Appendix F that we can run a modified AKM regression to identify the strength of the comparative advantage. This effect, however, turns out to be close to zero. Therefore, we can focus on workers' average skills, θ^i, which we obtain as the the average worker fixed effects from an AKM regression. We find that the average East German worker's unobserved skills are about 9 percentage points below those of a West German worker.[36]

Estimated Parameters and Targeted Moments. We are left with 23 parameters that are to be estimated. We impose two restrictions to reduce the parameter space. First, we set $A_{NE} = A_{SE}$ since average wages are similar in the Northeast and the Southeast.[37] Second, we assume that local amenities are the same, $\tau_{NE} = \tau_{SE} = \tau_E$. While these restrictions are not necessary for identification, they help reducing the degrees of freedom in the model, thus speeding up our estimation procedure. We show below that despite these restrictions, we match well the location-specific moments of the Northeast and Southeast.

We estimate the remaining 21 parameters through simulated method of moments, and target

[36] A recent literature has shown several concerns related to the estimation of second moments in AKM regressions (see Andrews et al. (2008), Andrews et al. (2012), and Bonhomme et al. (2019)). For our application, these concerns do not apply since we focus on first moments, which are unbiased (Andrews et al. (2008)).

[37] See Supplemental Appendix K.

the 305 moments summarized in Table 4.[38] Appendix E summarizes how each moment is computed.

Overall, we target all the key moments presented in the motivating evidence of Section 3, but for locations rather than regions. We then add a few more specific moments to discipline as well as possible the extent of labor market frictions.

The mapping between model and data is straightforward since we can compute exactly the same objects in both. The main complication is to define worker flows across locations in the data consistently with the model. A sizable share of individuals in our data report to be working in a location different from their residence, while in the model we do not distinguish between migration and commuting. As our baseline, we therefore count as migrants in the data all individuals that change their work location and satisfy either one of these conditions: i) they update their residence; ii) their new job is farther away from their residence than the old one and both jobs are within 200km of their residence (otherwise, we suspect that the residence is simply misreported).[39] We next describe how the moments identify our parameters.

Identification. Estimating the model requires us to separately identify the spatial frictions (κ^i_{jx}, τ^i_j, and z^i_{jx}) from the labor market frictions. Our strategy relies on the insight that labor market frictions mainly affect the allocation of labor within each location, and can therefore be identified from within-location moments, as quite standard in the Burdett-Mortensen framework (see, e.g., Bontemps et al. (2000)). Given the labor market frictions, the spatial frictions can then be inferred from the flows and wage gains of movers within and between regions, and how they differ by birth-place. While in practice all model parameters are jointly identified, we illustrate how we can identify the spatial frictions conditional on labor market frictions using both worker flows and wage gains in Figure 4, and list the associated moments in rows 1-4 of Table 4.[40] Each panel shows the mass of job offers with a given wage

[38] We estimate the model using a standard indirect inference approach and provide more details on our estimation algorithm in Appendix G. Figure A4 shows that the model likelihoods are locally single-peaked around each parameter estimate.

[39] About 7% of workers work in a location different from their residence. Defining cross-location movers as only those workers that change the location of their job and update their residence could overestimate spatial frictions since some job offers lead workers to commute, and hence these workers do not update their residence. However, since the living location is self-reported as discussed in Section 2, we do not want to include individuals that report to be living very far away from their job as these observations are likely misreported. We also do not want to define cross-location moves as all changes in work location regardless of residence since that could underestimate the frictions, as commuters, especially the ones moving back closer to their home, most likely do not pay the same fixed costs of relocating as migrants. Our definition strikes a balance between these concerns. In Supplemental Appendix T, we re-estimate our model with a broader and a narrower definition of cross-location moves and show that this mainly affects our estimates of the moving cost, while keeping most results unchanged.

[40] Since the job flows are also tied in steady state to the allocation of labor across locations, we target

Table 4: Targeted Moments

	Moments	N	Source	Model Fit	Key Parameters
(1)	Wage gains w/i locations, by (i, j)	16	Q.2.1	Fig 5	Σ, σ
(2)	Wage gains b/w locations, by (i, j, x)	48	Q.2.1	Fig 5	κ, τ_j^i, Σ
(3)	Job flows w/i locations, by(i, j)	16	Q.2.2	Fig 5	ϵ, ξ_0
(4)	Job flows b/w locations, by (i, j, x)	48	Q.2.2	Fig 5	z_{jx}^i, κ
(5)	Employment shares, by (i, j)	16	Q.2.3	Fig A8	κ, z_{jj}^i, τ_j, τ_j^i, z_{jx}^i
(6)	Unemployment shares, by (i, j)	16	Q.2.4	Fig A8	κ, z_{jj}^i, τ_j, τ_j^i, z_{jx}^i
(7)	AKM firm fixed effect by worker location and type, by (i, j)	15	Q.2.5	Fig A8	A_j, τ_j
(8)	AKM firm fixed effect, by j	3	Q.2.6	Fig A8	A_j, τ_j ,z_{jj}^i, τ_j^i
(9)	Relative output per worker, by j	3	Q.2.7	Fig A8	A_j, ν
(10)	Unemployment rates, by j	4	Q.2.8	Fig A8	ν
(11)	Deciles of firm-size distributions, by j	40	Q.2.9	Fig A9	ξ_1
(12)	Slope of wage vs firm size relationship, by j	4	Q.2.10	Fig A11	ξ_1 , ι
(13)	Slope of J2J wage gain vs initial wage, by j	4	Q.2.11	Fig A11	Σ, σ
(14)	Slope of separation rate vs firm wage, by j	4	Q.2.12	Fig A11	ξ_0 , σ, ϵ
(15)	Std of wage gains of movers, by (i, j, x)	64	Q.2.13	Fig A10	Σ, ξ_0 , ϵ, ι, σ
(16)	Profit to labor cost ratio, by j	4	Q.2.14	Table A8	σ, ξ_1 , ι,ξ_0, τ_j^i

Notes: The table reports the moments used in the estimation. The column titled "N" lists the number of moments in the group. Column "Source" links to the appendix section where the moment is computed, and column "Model fit" lists the table or figure that compares the empirical moment to the model-computed moment. The last column lists the key parameters that are pinned down by each set of moments as explained in Appendix G.

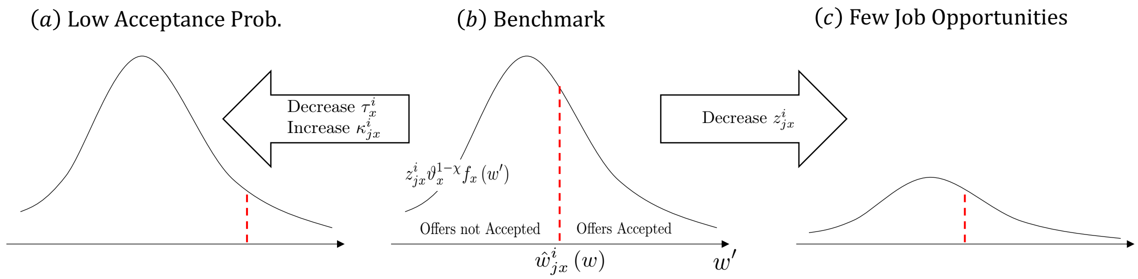
w' that is generated by a unit of search effort directed towards location x from location j, $z_{jx}^i \vartheta_x^{1-\chi} f_x(w')$.

To obtain intuition for our argument, assume that $\sigma \to 0$ so that an offer w' from location x is accepted by worker type i employed in region j at wage w if and only if $W_x^i(w') - \kappa_{jx}^i \geq W_j^i(w)$. Let $\hat{w}_{jx}^i(w)$ be the cutoff wage offer such that $W_x^i\left(\hat{w}_{jx}^i(w)\right) - \kappa_{jx}^i = W_j^i(w)$. The accepted offers are the ones to the right of $\hat{w}_{jx}^i(w)$, and the mass of worker flows per unit of search effort is the integral under the wage offer density to the right of $\hat{w}_{jx}^i(w)$. Starting from the benchmark (b), we consider a decrease in the search efficiency z_{jx}^i in panel (c). This decrease reduces the mass of offers received, and hence the worker flows. However, it does not affect the cutoff $\hat{w}_{jx}^i(w)$, and hence has no effect on the average wage gain of workers that accept an offer.

In contrast, a decline in workers' preference for location x, τ_x^i, shifts the acceptance threshold to the right in panel (a) (a similar argument applies to a rise in the moving cost, κ_{jx}^i). Therefore, a worker accepts only relatively better offers. Hence, the expected wage gain of a

those moments as well (rows 5-6).

Figure 4: Identifying Spatial Frictions



move increases in κ_{jx}^i and decreases in τ_x^i. Wage gains between locations are thus informative of κ_{jx}^i and τ_x^i, while flows between locations primarily help identify z_{jx}^i.[41]

Without further restrictions, we cannot separate moving costs κ_{jx}^i from location preferences τ_x^i. To obtain identification, we assume that moving costs are identical for all worker types. We can then identify the location preferences using differences in wage gains for individuals of different types that make the same migration move, e.g., East versus West Germans that move from East to West.[42]

We now discuss the remaining parameters. The productivity shifters (A_j) and the search efficiency of the unemployed (ν) are mainly related to the average firm wages, output per worker and unemployment by location (rows 7-10). When productivity is higher, firms offer a higher wage, everything else equal. A greater search efficiency of the unemployed reduces the unemployment rate and increases output per capita. The moments are also related to the location's amenity (τ_j), which leads to lower wages due to compensating differentials.

The variance of firm productivity (Σ), the labor market friction parameters $(\xi_0, \xi_1, \epsilon, \sigma)$, and the level of the reservation wage relative to firm productivity (ι) are linked to the efficiency of the job ladder (rows 11-15). This is expected: a higher variance of productivity raises the variance of wages; ξ_0 and ξ_1 determine the intensity of vacancy posting and how it varies across firms; the cost of search effort ϵ modulates the relationship between workers' search intensity and the value of employment at their current firm; and σ determines how much the job moves are directed towards higher wage offers, hence affects movers' mean and variance of wage gains.

Finally, the labor market friction parameters (σ, ξ_0, ξ_1) and the reservation wage (ι) are

[41] As mentioned, since in our data we can only observe workers in a new location once they have a job, we assume in the model that workers can only move across locations after having received a job offer. If, in practice, workers move to a new location to search for jobs while still unemployed, the model is going to capture any mobility barrier that they may face through a lower search productivity z_{jx}^i.

[42] Supplemental Appendix R includes analytical expressions for the main targeted moments (wage gains and separation rates) and provides a further discussion of identification.

related to firm profitability (row 16). Greater labor market frictions increase firms' local monopsony power and hence profit margin, while a higher reservation wage decreases profitability. The home preference τ_j^i also plays a role: when workers are more attached to a location, firms face less competition from other locations.

Since in practice all parameters are jointly identified, we verify our heuristic identical argument in the full estimation via model simulations and show the Jacobian matrix illustrating the elasticity of each (model generated) moment to each parameter in Appendix G. The last column of Table 4 reports the most important parameters for each moment based on this exercise.[43] Furthermore, still in Appendix G, we generate moments from the model using random parameter values and show that our procedure correctly recovers these parameters, building further confidence in our estimation.

The Jacobian matrix confirms the importance of targeting both wage gains and workers flows across locations to identify the spatial frictions. The wage gains between locations (row 2 of Table 4) are crucial for the moving costs κ and the preference τ_j^i, while the job flows between locations (row 4) are important for the relative search efficiencies z_{jx}^i. The spatial frictions are also key for the steady state allocation of employed and unemployed workers (rows 5-6). As expected, the within-location wage gains and flows (rows 1 and 3) are not relevant for the spatial frictions. Large within-location wage gains are driven by either a large variance of productivity (Σ), or a low variance of the taste shock (σ) so that workers only accept job offers with an associated wage increase. Within-location flows are related to the parameters of the costs of applying to jobs (ϵ) and of posting vacancies (ξ_0).

5.2 Results

Next, we turn to the results, show the model fit, and discuss the parameter estimates.

Model Fit. The left panel of Figure 5 plots the wage gains of job-to-job movers in the data against those in the model, while the right panel shows the labor flows.[44] Each dot is for one of the 64 different types of moves by origin-destination-home location. The model matches the data well. For example, it generates larger wage gains for moves towards the West (blue

[43] Since the full Jacobian matrix includes 6,405 (305×21) cells, in our exposition we take averages of the 16 blocks of moments shown in Table 4 and show these averages rather than each moment separately. In the table and graph, we bundle together a few sets of closely related parameters and refer to them jointly as follows: i. the two relative amenities τ_{SW} and τ_E (we refer to them jointly as $\tau_j \equiv \{\tau_{SW}, \tau_E\}$); ii. the two home biases τ_l and τ_r $\left(\tau_j^i \equiv \{\tau_l, \tau_r\}\right)$; iii. the relative search efficiencies between regions z_0, z_1, $z_{l,2}$ and z_r $\left(z_{jx}^i \equiv \{z_0, z_1, z_{l,2}, z_r\}\right)$; iv. the cost of moving κ_0 and κ_1 ($\kappa \equiv \{\kappa_0, \kappa_1\}$); v. the two relative productivities A_{SW} and A_E ($A \equiv \{A_{SW}, A_E\}$); vi. the two costs of vacancy posting $\xi_{0,W}$ and $\xi_{0,E}$ ($\xi_0 \equiv \{\xi_{0,W}, \xi_{0,E}\}$).

[44] For brevity, we present the model fit in figures in the main draft. In Supplemental Appendix U, we list all the targeted and estimated moments explicitly.

symbols). Individuals are also more likely to move within-location (gray circles) and to move back to their home location and region (diamonds) than away from home (stars). As in the data, there is significant heterogeneity in wage gains across locations even for within-location moves, due to different local wage distributions and differences in the composition of worker types.

We discuss the fit of all other moments in Appendix H, and summarize here the takeaways. The model matches well the steady state distributions of workers and the average GDP, wages, and unemployment rates, consistent with the hypothesis that the German labor market is in steady state. The model's job ladder mechanism implies that more productive firms offer higher wages and have a lower rate of quits, which allows the model to do a reasonable job in matching the empirical joint distribution of firm wages, sizes, and separation rates, as well as the standard deviations of the wage gains of job movers and firms' profit shares. The model somewhat overestimates the relationship between firm wage and firm size, and generates a smaller standard deviation of wage gains of movers than the data. These results are possibly expected: in the model, wage dispersion across firms is purely generated by labor market frictions, while in the data there may be other sources of wage dispersion that our empirical controls are not capturing.[45]

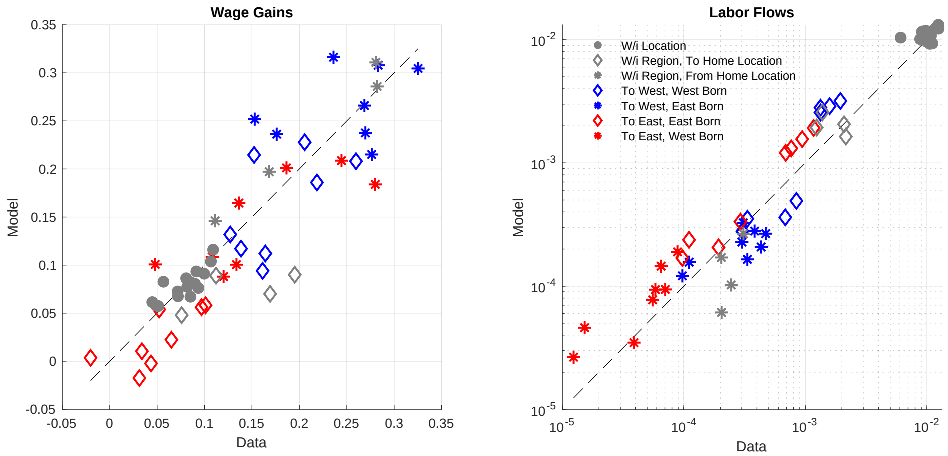
Overall, the fit is good considering that we estimate 21 parameters to target 305 moments.[46] Several structural restrictions imposed by the model on the joint distributions of firm wages, employment, wage gains, and labor flows are satisfied in the data, building confidence in our estimated frictions.

Parameter Estimates. We present the estimated spatial frictions in Table 5, and include the remaining parameters in Appendix G. Row 1 reports the one-time moving costs, κ_{jx}, as a fraction of the present discounted value of income. Since these costs vary with distance, we present a range for moves between the closest two locations and moves between the farthest two locations. We find moving costs in the range of $3-5\%$ of the PDV of income. Rows 2 and 3 show a strong preference for birth-location: workers need to be paid about 7.4% more than in their home location to obtain the same flow utility, and moving towards the

[45]In Figure A11 we show the non-parametric relationships for the moments in rows 12, 13, and 14 of Table 4. In Figure A10, we show that adding individual fixed effects in wage growth brings the empirical estimates for the standard deviations of wage growth very close to the model's ones.

[46]Given the arbitrary distinction between targeted and not targeted moments, we decided to simply include as targets all relevant moments. The model performance is thus evaluated by its ability to simultaneously match several features of the data despite its relatively limited flexibility. We list in Table 4 for each parameter the key moments that identify it.

Figure 5: Wage Gains and Frequency of Job Flows



Notes: The left panel shows the average wage gains of different types of job-to-job moves in the data (x-axis) against the average wage gains in the model (y-axis). The right panel shows the frequency of each type of job-to-job move in the data (x-axis) against the frequency in the model (y-axis). Different types of moves are identified by a mix of colors and symbols, listed in the right panel. In total, there are 64 possible types of moves by origin location, destination location, and home location. The data moments are listed in Appendix E.

non-home region would require a yearly compensation of almost 10%.[47,48]

Rows 4 and 5 report the search efficiencies, relative to the within-home location level, which is normalized to 100%. Search efficiency is much lower across locations, consistent with evidence that workers search for jobs primarily locally.[49] For example, row 5.i shows that one unit of search effort expended across locations to the non-home region translates into filing only about 1/20th as many applications. Search is also more efficient towards the home location (compare 5.i and 5.iii), possibly reflecting social connections (Burchardi and Hassan (2013), Bailey et al. (2020)).

We discuss the remaining parameters in Appendix G. We note that our model infers an amenity value in the East that is 11% higher than in the West. This additional amenity is consistent with the large fiscal transfers towards East Germany (Henkel et al. (2021)) and it could additionally reflect remaining cost of living differences that are not picked up by our price indices.

[47] Our estimated moving and preference costs are consistent with the findings in Schmutz and Sidibé (2018), who estimate moving costs between 13,700 € and 16,900 € between cities in France. The moving costs we estimate are smaller than in work that does not account for a frictional labor market, for two reasons: first, since any cross-location move is also a move between firms, part of the wage gain from migration reflects general labor market frictions that are also present within region, rather than moving costs; second, the search frictions across locations in our model allow us to match a low cross-regional migration rate without the need of a very large moving cost.

[48] In Supplemental Appendix V, we explore one potential source of home preferences using the SOEP. We show that workers' likelihood of moving back home increases sharply after the birth of a child, possibly highlighting the importance of family ties.

[49] Manning and Petrongolo (2017), Le Barbanchon et al. (2020), Datta (2022).

Table 5: Estimated Spatial Frictions

Moving Costs $\{\kappa\}$			
(1)	Moving cost as share of PDV of income: $\kappa_0 e^{\kappa_1 dist_{jx}}$ (b/w closest to b/w furthest locations)		3.12% to 5.31%
Preferences $\{\tau\}$			
(2)	Cost of not living in the home location, as share of income: τ_l		7.41%
(3)	Cost of not living in the home region, as share of income: τ_r		9.88%
Relative Search Efficiency $\{z\}$			
(4)	w/i location, away from home location: $1 - z_{l,1}$		90.52%
(5)	b/w locations (closest to furthest locations)	5.i) not to home region: $z_0 e^{-z_1 dist_{jx}}$	6.10% to 4.95%
		5.ii) to home region: $\left(z_0 e^{-z_1 dist_{jx}}\right)(1 + z_r)$	7.32% to 5.23%
		5.iii) to home location: $\left(z_0 e^{-z_1 dist_{jx}}\right)\left(1 + z_{l,2}\right)$	24.11% to 17.22%

Notes: The table shows the estimated values of the spatial frictions. All parameters used to compute them, according to the formula included in each row, are in Table A7. Row 1 provides a range of the estimated moving costs, ranging from costs for moves between the closest two locations to moves between the furthest two locations. Rows 2-3 present the values of the estimated preference parameters. Search efficiencies in rows 4 and 5 are expressed as a percentage of the efficiency within the home location, z^j_{jj}, which is normalized to 1. Rows 5i-5iii show the efficiencies for searching across locations outside of the home region, in the home region but not the home location, and in the home location, respectively. The efficiencies are again reported as a range for searching between the two closest locations to searching between the two furthest locations.

Discussion. Our results hinge on two core assumptions of the Burdett-Mortensen framework: wage posting and random search.

The wage posting protocol implies that firms cannot discriminate based on workers' type or current location. This assumption is supported by recent evidence that the outside option has a limited effect on workers' wages (Jäger et al. (2020)) and that, conditional on the current firm, a worker's previous firm has almost no effect on current wages (Kline et al. (2019)). Nonetheless, we note that under a different wage setting method larger wage gains for movers between locations could be driven by firms offering wage premia to compensate workers that have to migrate to take a job. In our framework, these premia would be identified as moving costs as long as they are common across workers.

Random search within location implies that, for any given application, workers are equally likely to draw offers from each firm in the distribution. Since we do not observe offers received, this is an unverifiable assumption. It affects the interpretation of the search efficiencies z^i_{jx}. For example, lower observed flows from location j to location x could be driven not by a low search efficiency, but by workers i employed in location j being more likely to sample from the left tail of the distribution in location x. While our assumption is strong, it does not affect the overall meaning of z^i_{jx}: whether workers receive fewer or worse offers from a particular location, they still have a hard time accessing job opportunities, hence a low search efficiency. A related assumption of our model is that only workers can direct their search effort towards locations, while firms cannot post vacancies targeted to a specific labor market. This is an identifying assumption driven by the fact that, given our data, we cannot distinguish between firms' or workers' behavior in generating matches.

6 Labor Misallocation across Firms and Regions

We now use the estimated model to study the role of spatial frictions in (mis)allocating labor across firms and regions. First, we study the aggregate effects of spatial frictions. Then, we turn to the distributional effects across regions and workers' types. Finally, we show that the impact of spatial frictions on the economy depends on the size of labor market frictions. Since the heterogeneity across locations within regions is small relative to the East-West differences, we aggregate the results by region rather than showing individual locations throughout this section.[50]

6.1 Aggregate Effects of Spatial Frictions

We recompute the equilibrium keeping all the parameters at their estimated values, but removing the spatial frictions: the moving cost ($\kappa_0 = 0$), the home preferences ($\tau_l = \tau_r = 0$), and the differences in search efficiency across and within locations ($z_{l,1} = z_{l,2} = z_r = z_1 = 0$ and $z_0 = 1$). For these counterfactuals we keep the unemployment benefit b_j^i fixed at its estimated baseline value (rather than estimating it to match the reservation wage), and allow equilibrium prices to respond to local GDP (rather than using their empirical values). The fixed b_j^i implies that some firms that posted vacancies in the baseline may no longer do so in the counterfactual, generating endogenous exit. We compute four core statistics for the baseline and the counterfactual long-run steady state equilibrium: (i.) output per worker (Y); (ii.) the average of workers' value functions across all employed and unemployed workers; (iii.) average real wage, $w_j(p)\,\theta_j^i/P_j$; and (iv.) the share of the overall employment in West Germany.[51]

The results are shown by the first set of blue bars in Figure 6. Removing all spatial frictions leads to an increase in output per worker of slightly less than 5%.[52] Despite these relatively modest output gains, the increase in the average worker's value is much larger.[53] The reason

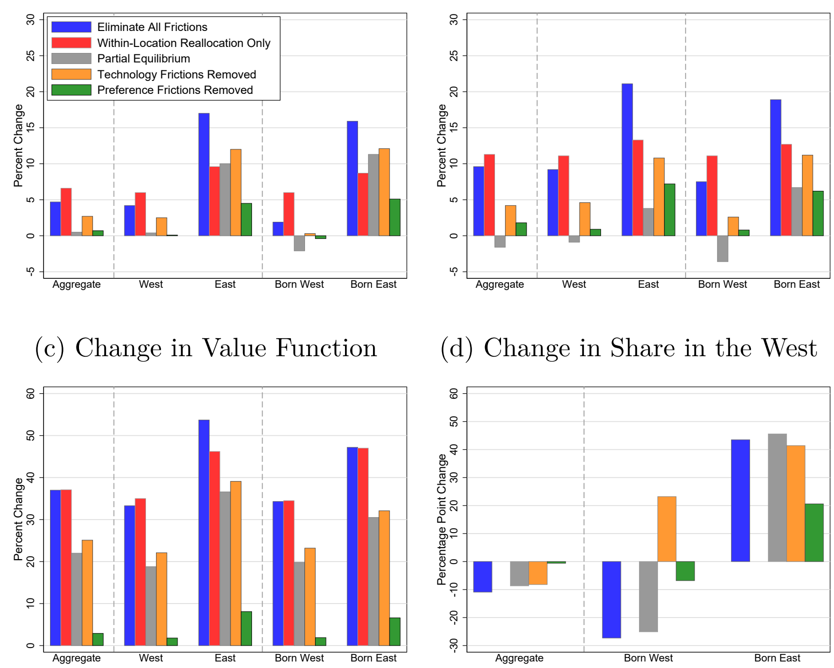
[50] We present results by location in Supplemental Appendix W.

[51] We present additional statistics, such as the change in unemployment, in Supplemental Appendix W.

[52] The aggregate productivity cost of spatial frictions is smaller in our model than in other contexts (e.g., Bryan and Morten (2019)), which is likely due to the different context (developed versus developing country) and due to the fact that our model does not contain a key mechanism in their work, namely that each individual draws a vector of location-specific comparative advantages.

[53] We use the term workers' value rather than welfare since we are, in the counterfactual, effectively changing preferences through the taste spatial friction τ_j^i.

Figure 6: Aggregate and Distributional Effects of Removing Spatial Frictions



(a) Change in Output per Worker

(b) Change in Real Wage

(c) Change in Value Function

(d) Change in Share in the West

Notes: Figure shows the effects of various exercises, shown with the different-colored bars, on four outcomes: output per worker (top-left), real wage (top-right), average value (bottom-left), and the share of workers in the West (bottom-right). Bars show percentage change relative to the baseline economy.

is twofold. First, without spatial frictions workers no longer incur the moving cost κ^i_{jx} or the utility cost (τ_l, τ_r) when they cross locations. Moreover, workers' search efficiency across locations rises. These factors lead to a higher continuation value. Second, eliminating spatial frictions exposes firms to stronger competition for workers from other locations, which raises wages more than labor productivity due to a reduction in firms' monopsony rents.

The bottom right panel illustrates that there is net reallocation of labor towards the East, hence, towards the region with, on average, lower productivity. This result could seem counterintuitive: in a neoclassical framework we would have expected labor to reallocate towards the West. However, it is a direct implication of an inherent asymmetry in our frictional setting. In the data, and in our baseline estimation, there are only about a third as many East Germans as West Germans. Therefore, there are more West German workers affected by home bias than East German ones. Once we eliminate spatial frictions this home attachment is removed, allowing a larger absolute number of West Germans to migrate than the other way around, even though in relative terms West Germans are less likely to move regions than East Germans.

We now further investigate the mechanisms behind these findings in our model with worker allocation both across firms and locations. First, we analyze the importance of within-location reallocation of labor compared to worker reallocation across locations. Second, we discuss the role of the equilibrium response of firms. Third, we separately analyze the different types of frictions.

The Importance of the Within-Location Allocation of Labor. Our first key result is that the aggregate gains we find arise from a better allocation of labor *within* locations, rather than from migration of workers towards high productivity locations. To reach this result, we recompute the aggregate gains holding fixed the share of workers of each type in each location (fixing $\bar{e}_j/\bar{e}$ in equation (20)) at the baseline level. We continue to change the within-location distribution of workers and firms' policy functions as in the full counterfactual, thus changing Y_j. The results, in the red bars in Figure 6, show that shutting down the migration across locations actually *raises* output and wages, since in the full counterfactual workers migrate towards the lower productivity East.

Panel (a) of Figure 7a analyzes how the within-region reallocation of workers generates the aggregate gains by presenting CDFs of employment to firms of different productivity within East and West Germany.[54] Removing spatial frictions shifts the distributions to the right as labor reallocates towards the more productive firms. In the baseline economy, spatial frictions partially shield low productivity firms from competition through two margins: i.) by reducing the value of unemployment, thus allowing firms to hire workers at a relatively low wage; ii.) by limiting the rate at which workers are poached, as they are only rarely poached from firms in the other region. As spatial frictions are removed, these protections are eliminated. Therefore, it becomes harder for unproductive firms to hire and to retain workers, forcing them to shrink, and some firms stop posting vacancies altogether. While removing spatial frictions also makes it easier for unproductive firms to hire from the other region, on net the negative effect dominates. This effect is stronger in the East because it has the lowest productivity firms overall.

Using equation (21), we can decompose the total labor of a firm of productivity p in region j as

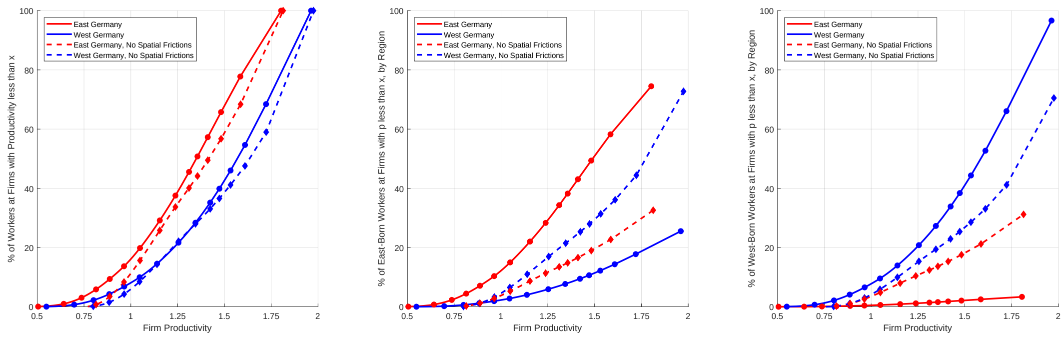
$$e_j\left(p\right) = \underbrace{\vartheta_j^{-\chi}}_{\text{Tightness}} \quad \underbrace{v_j\left(p\right)}_{\text{Vacancies}} \quad \sum_{i \in \mathbb{I}} \left(\left(\frac{\bar{a}_j^i}{\bar{a}_j}\right) \underbrace{\left(\frac{\mathcal{P}_j^i(w(p))}{q_j^i(w(p))}\right)}_{\text{Job Appeal}} \right).$$

Market tightness and the share of applications by type only affect the allocation of labor between regions since they do not depend on p. The other terms could, in principle, explain the reallocation of labor towards more productive firms. Removing spatial frictions might

[54] Since the baseline was estimated from the data moments, it is consistent with the within-region wage distributions shown in Figure 1b if wages are increasing in productivity, as in our model.

Figure 7: Labor Allocation Across Firms and Regions

(a) All Workers (b) East Germans (c) West Germans



Notes: The left panel shows the CDF of workers over firm productivity within East (in red) and West Germany (in blue). The solid line is our benchmark estimation, while the dashed one the counterfactual without spatial frictions. The middle panel is a semi-CDF that shows the distribution of employment for East German workers across the whole Germany. To interpret the figure, consider that, at baseline, more than 75% of employment is in East Germany, and the remaining employment is in the West (i.e., the two last points of the solid lines add up to one, and similar for the dashed lines). The right panel shows the semi-CDF for West Germans.

allow high productivity firms to post relatively more vacancies (high $v_j(p)$), make it easier for them to attract workers upon meeting them (high $\mathcal{P}_j^i(w)$), or facilitate worker retention (low $q_j^i(w)$).

In Figure 8, we plot these three objects as a function of firm productivity.[55] Panel (a) shows that the number of posted vacancies contributes positively to the reallocation of labor from low- to high-productivity firms. As discussed in Section 4.3, when spatial frictions are removed more productive firms increase their number of vacancies and unproductive firms shrink. The least productive firms post zero vacancies and become inactive, generating endogenous exit via the vacancy adjustment.[56] The separation rate also contributes to the improved allocation of labor (panel (c)): in the counterfactual equilibrium all workers search more intensively, leading to a higher separation rate than in the baseline, but this effect is larger at lower productivity firms. The acceptance probability, instead, mitigates the reallocation gains (panel (b)). Workers are relatively more likely to accept offers at lower productivity firms in the economy without spatial frictions. This result is driven by the fact that access to the country-wide pool of unemployed workers, as previously noted, has a larger relative impact on the lower productivity firms.[57]

Large Equilibrium Effects due to Lower Monopsony Power. Our second key result is that the majority of the aggregate gains arise from the change in labor market competition

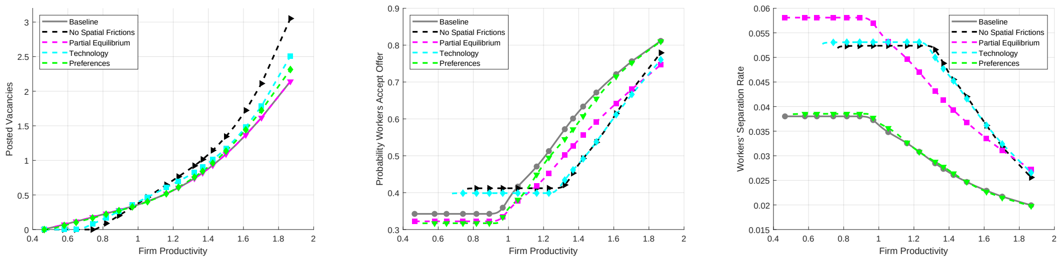
[55] Plots are for East Germany. The ones for the West are similar and are in Supplemental Appendix W.

[56] As is standard in this class of models, each vacancy could be interpreted as a single position firm.

[57] For the higher productivity firms, instead, the probability that an offer is accepted decreases due to the overall improvement in the allocation of labor and the increased effective competition.

Figure 8: Margins of Employment in East Germany

(a) Posted Vacancies (b) Acceptance Probability (c) Separation Rate



Notes: All panels are for firms in East Germany and show outcomes as a function of firm productivity. The left panel shows the change in the number of posted vacancies. The middle panel shows the probability that a given wage is accepted by the worker it matches with. The right panel shows the monthly rate at which workers separate towards either other firms or unemployment. We consider four possible counterfactuals, described in text.

and the resulting decline in firms' local monopsony power, rather than from changes in workers' behavior. In the counterfactual equilibrium, both workers and firms adjust. Workers search more intensively across locations and are more willing to accept job offers that are further away. Firms adjust their wages and vacancies to more competition. To disentangle these two effects, we recompute the steady state holding fixed firms' wages and posted vacancies at their baseline values while allowing workers to adjust their search and acceptance behavior.

The first set of gray bars in Figure 6 show that when firms' wage and vacancy policies are held fixed, the output per capita increases by only 0.5%. Thus, firms' equilibrium response to more competition is the main driver of the aggregate gains. Intuitively, when firms are not able to adjust vacancies, one of the key drivers of the improved within-allocation is muted, as illustrated by the dashed pink line on top of the gray line in Panel (a) of Figure 8.[58] While the separation rate still rises more for low-productivity firms than for high-productivity ones (Panel (c)), this channel alone has only a modest effect.

Effects of Individual Frictions. Our third finding is that there are strong complementarities between the *technological* spatial frictions imposed by the moving cost κ and the search productivity z, and *preference* spatial frictions due to home preferences τ. Technological frictions could be affected by policy, for example by a faster railway system or an integrated online job portal. Instead, preference frictions are plausibly harder to affect, as they are typically a slow moving object (Alesina and Fuchs-Schündeln (2007)). To analyze their effects separately, we recompute the equilibrium of the economy when we remove either only the technological spatial frictions or the home preferences. The yellow and green bars in Figure 6 show that removing technological barriers alone generates aggregate gains that are about

[58]In Supplemental Appendix W we replicate Figure 7 for this alternative counterfactual.

a third to one half as large as the baseline. In contrast, removing home preferences generates only modest gains. Addressing both types of frictions jointly is important: summing over the aggregate gains from both separate exercises yields only about half the effect of removing both sources of frictions at the same time.

Evidence of Our Mechanism. Our findings rely on a key mechanism: lower spatial frictions increase competition, which improves allocative efficiency by forcing inefficient firms to shrink or to exit the market. While we do not have direct evidence on the response of firms' wage and vacancy policies, we can bring indirect evidence to test our mechanism. Specifically, we study the relationship between spatial frictions and workers' reservation wage and search effort, which can be observed in the U.S. Survey of Consumer Expectations (SCE). See Appendix I for details.

We verify three implications of the model. First, workers that commute longer distances conditional on a given wage, hence are effectively more exposed to spatial frictions, spend more time searching for a new job and send more applications, consistent with a "local firm advantage".[59] Second, workers at the bottom of the local pay distribution search more for new jobs for a given commuting time, supporting the notion that low-wage firms are most affected by spatial frictions. Third, conditional on their current wage workers have a higher reservation wage when their local labor market has more job opportunities, and hence local economic conditions matter.

Role of Number and Size of Locations. In Appendix J, we explore the quantitative role of two features of our model: (i.) there are only two locations in each region; (ii.) the locations in East Germany are smaller, hence have fewer firms and workers. We increase the number of locations to 24 (12 in each region), and show that there are still large gains from the within-location reallocation of labor. Thus, our results are not driven by the relatively small number of locations in the model. Moreover, we show that changing the relative size of the labor force in each location changes the aggregate effects only slightly.

6.2 Distributional Effects of Spatial Frictions

We next focus on the distribution of resources across regions and worker types.

Differences by Region. The second and third set of blue bars in Figure 6 examine the effects of removing all spatial frictions separately for individuals in the West and in the East of Germany.[60] The baseline gains are larger in the East than in the West, for two reasons.

[59] Workers also search more intensively for a new job when they are "less satisfied" with the current one. This variable captures potential non-pay amenities of the job ladder.

[60] In the model, individuals move continuously across locations. Nonetheless, we can compute the outcomes for the individuals that are, in our long-run steady state, in either East or West Germany. The statistics

First, despite similar observables, we estimated a large gap between East and West workers in unobservable skills (see row 1 of Table 3). Therefore, as West workers move East and East workers move West, relative human capital improves in the East. Second, the reallocation of labor away from lower productivity firms is stronger in the East since there are more low productivity firms in that region.

While East Germany gains the most, output and wages also rise in West Germany. This outcome differs from a neoclassical benchmark model with one representative firm in each region, where eliminating barriers to labor mobility would lead to net worker flows towards the West until marginal labor productivity is equalized across regions. In our model with heterogeneous firms, workers in the West gain since there is net reallocation of labor towards the East, hence a less tight West German labor market, and, moreover, an improvement in the within-region allocation of labor.

In our second exercise (red bars), we find that when migration across regions is shut down, the output and wage gains in East Germany fall by nearly half. Intuitively, a large part of the East German gains is due to the increase in average human capital due to the in-migration of West German workers. Instead, in West Germany, migration has a negative effect on output and wages. Due to the importance of migration, the partial equilibrium gains (gray bars) in East Germany are also relatively large.

Differences by Worker Type. The fourth and fifth set of bars in Figure 6 compare the effects of removing spatial frictions for East and West Germans. While everyone benefits, East Germans see a larger increase in their output per capita and wages since a sizable share of them move from the East to the high productivity West. Panel (b) of Figure 7 illustrates this move by plotting the semi-CDF of East Germans in each region.[61] The share of East Germans in the West rises significantly.

West Germans, as shown in Panel (c) of Figure 7, migrate on net towards the less productive East. Nonetheless, their wage rises because of the equilibrium increase in average wage in both regions, and from the overall improvement in the allocation of labor within region.

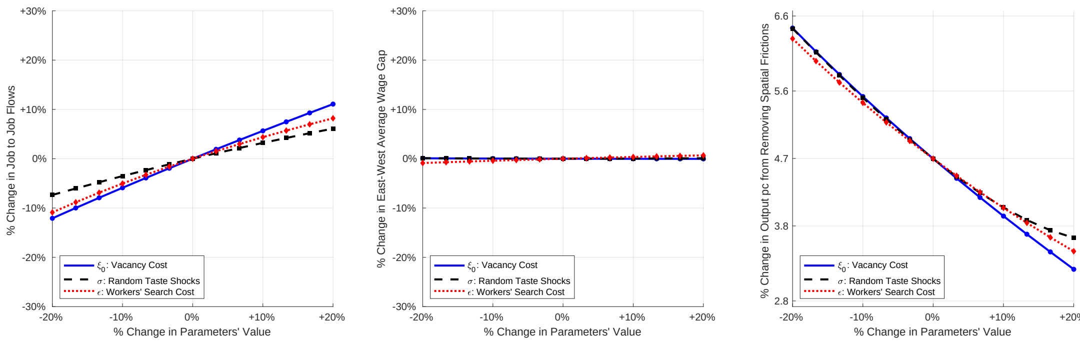
Implications for the West-East Gaps. We show in Appendix J that eliminating spatial frictions shrinks the gaps in output, value, and real wages between East and West Germany to 16%, 0.4%, and 14%, respectively. The remaining gaps are due to the average higher productivity of firms in the West, the higher estimated amenity in the East, and the presence of labor market frictions. The higher amenity in the East allows firms there to still retain

account for the possibility that individuals move across locations and regions.

[61]Note that each line does not end at one but at the share of East German workers in each region. Adding up the last points on the two solid lines or on the two dashed lines gives one.

Figure 9: Sensitivity of Micro and Macro Moments to Labor Market Parameters

(a) Within-Location Job Flows (b) East-West Wage Gap (c) Output per Capita Gains



Notes: We vary three different parameters modulating the labor market frictions, recompute selected targeted moments, and compare them with the baseline economy. The left panel shows the job to job flows (the lines marked with a cross are the job flows within region) relative to the baseline. The middle panel shows the change in the gap in average wage between West and East Germany relative to the baseline. The right panel shows the overall effect on GDP per capita.

workers while paying a lower real wage.

6.3 The Role of the Local Labor Market for Aggregate Gains

Our final key result is that the micro-level details of the labor market matter for the gains of removing spatial frictions due to their impact on the allocation of labor across firms. To show this result we vary, one at a time, three core labor market frictions: (i.) the vacancy cost (ξ_0), which affects the overall mass of vacancies posted by firms; (ii.) the variance of the preference taste shocks (σ), which affects the allocative power of wages; (iii.) the elasticity of workers' search cost (ε), which modulates the ability of workers to move up the job ladder.

Panel (a) of Figure 9 shows that within-location job-to-job flows increase relative to the baseline as we raise each parameter, leading to more within-location reallocation. However, as Panel (b) highlights, changing the labor market frictions has no significant effect on the aggregate wage gap between East and West Germany, consistent with the idea that labor market frictions mainly affect the distribution of labor within, rather than between, regions. In Panel (c), we compute, just as in Section 6.1, the aggregate gains from removing spatial frictions as we vary the degree of labor market frictions in the economy. The aggregate gains in output per capita decline substantially as within-location labor mobility increases. For example, in an economy with 10% higher vacancy costs, the aggregate gains are reduced by a quarter compared to the baseline, from 4.7% to 3.9%.[62] This result is intuitive: with

[62] It is possibly surprising that the effect of varying each source of labor market frictions in panel (c) is similar. There is no fundamental reason why this should be the case, and it is due to the fact that all three frictions have similar impact on labor mobility as shown in Panel (a).

more within-location mobility, labor is already relatively concentrated at the most productive firms, hence the marginal gains from additionally removing spatial frictions are limited. This result is also important: ignoring within-location reallocation can lead to wrong assessments about the importance of spatial frictions. Two economies could look identical in terms of their regional wage gaps, yet removing spatial frictions could lead to very different aggregate outcomes dependent on labor market frictions.[63]

7 Conclusion

In this paper, we have shown that taking into account the within-region heterogeneity across firms, and the extent of local labor market frictions, is important to quantify the costs of spatial barriers on the aggregate economy and to understand the mechanisms through which they operate. To reach this conclusion, we design a model which encompasses both spatial and labor market frictions, allowing us to study the joint allocation of labor across firms and locations. Bringing the model to data from Germany, we learn four insights that are relevant beyond this specific context.

First, removing spatial frictions can improve the allocation of workers within locations, leading them to concentrate towards more productive firms and generating aggregate gains. Second, these aggregate gains can be primarily the result of an equilibrium response of firms to the change in the competitive environment: removing spatial frictions increases the local competition for workers and diminishes firms' local monopsony power. As a result, workers reallocate towards the most productive firms, which are less affected by the increased competition for workers. Third, the aggregate gains from removing spatial frictions can vary substantially across economies dependent on their local labor market frictions, even when these economies have the same wage gap between locations. Analyzing spatial wage gaps without firm-level data may therefore give an incomplete picture. Finally, even in a context, such as ours, in which the within-location reallocation of workers is important for the aggregate gains, reallocation across regions is still important for the distributional effects, as workers born in a low productivity locations are trapped there by spatial frictions.

[63] In Supplemental Appendix W we present additional plots of job-to-job movers' average wage gains, the change in workers' value, and East Germans' real wage increase.

References

Abowd, John, Francis Kramarz, and David Margolis (1999). “High Wage Workers and High Wage Firms”. In: *Econometrica* 67.2, pp. 251–333.

Alesina, Alberto and Nicola Fuchs-Schündeln (2007). “Good-bye Lenin (or not?): The effect of communism on people’s preferences”. In: *American Economic Review* 97.4, pp. 1507–1528.

Allen, Treb and Costas Arkolakis (2014). “Trade and the Topography of the Spatial Economy”. In: *The Quarterly Journal of Economics* 129.3, pp. 1085–1140.

Andrews, Martyn J, Len Gill, Thorsten Schank, and Richard Upward (2008). “High wage workers and low wage firms: negative assortative matching or limited mobility bias?” In: *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 171.3, pp. 673–697.

Andrews, Martyn J, Leonard Gill, Thorsten Schank, and Richard Upward (2012). “High wage workers match with high wage firms: Clear evidence of the effects of limited mobility bias”. In: *Economics Letters* 117.3, pp. 824–827.

Bachmann, Rüdiger, Christian Bayer, Heiko Stüber, and Felix Wellschmied (2021). “Monopsony Makes Firms not only Small but also Unproductive: Why East Germany has not Converged”. mimeo.

Bagger, Jesper and Rasmus Lentz (2019). “An empirical model of wage dispersion with sorting”. In: *The Review of Economic Studies* 86.1, pp. 153–190.

Bailey, Michael, Patrick Farrell, Theresa Kuchler, and Johannes Stroebel (2020). “Social connectedness in urban areas”. In: *Journal of Urban Economics*, p. 103264.

Baum-Snow, Nathaniel and Ronni Pavan (2012). “Understanding the city size wage gap”. In: *The Review of economic studies* 79.1, pp. 88–127.

BBSR (2009). “Regionaler Preisindex”. In: *Berichte*. Vol. 30. Bonn: BBSR.

Berger, David, Kyle Herkenhoff, and Simon Mongey (2022). “Labor market power”. In: *American Economic Review* 112.4, pp. 1147–93.

Bilal, Adrien (2023). “The geography of unemployment”. In: *The Quarterly Journal of Economics* 138.3, pp. 1507–1576.

Bilal, Adrien G, Niklas Engbom, Simon Mongey, and Giovanni L Violante (2022). “Firm and worker dynamics in a frictional labor market”. In: *Econometrica* 90.4, pp. 1425–1462.

Bird, Richard and Enid Slack (2002). “Land Taxation in Practice: Selected Case Studies. Germany.” World Bank Conference on Innovations in Local Revenue Mobilization.

Boeri, Tito, Andrea Ichino, Enrico Moretti, and Johanna Posch (2021). “Wage equalization and regional misallocation: evidence from Italian and German provinces”. In: *Journal of the European Economic Association* 19.6, pp. 3249–3292.

Bonhomme, Stéphane, Thibaut Lamadon, and Elena Manresa (2019). “A distributional framework for matched employer employee data”. In: *Econometrica* 87.3, pp. 699–739.

Bontemps, Christian, Jean-Marc Robin, and Gerard J Van den Berg (2000). “Equilibrium Search with Continuous Productivity Dispersion: Theory and Nonparametric Estimation”. In: *International Economic Review* 41.2, pp. 305–358.

Bradley, Jake, Fabien Postel-Vinay, and Hélène Turon (2017). “Public Sector Wage Policy and Labor Market Equilibrium: A Structural Model”. In: *Journal of the European Economic Association* 15.6, pp. 1214–1257.

Bryan, Gharad and Melanie Morten (2019). “The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia”. In: *Journal of Political Economy*.

Burchardi, Konrad B and Tarek A Hassan (2013). “The economic impact of social ties: Evidence from German reunification”. In: *The Quarterly Journal of Economics* 128.3, pp. 1219–1271.

Burdett, Kenneth, Carlos Carrillo-Tudela, and Melvyn Coles (2020). “The cost of job loss”. In: *The Review of Economic Studies* 87.4, pp. 1757–1798.

Burdett, Kenneth and Melvyn Coles (2003). “Equilibrium wage-tenure contracts”. In: *Econometrica* 71.5, pp. 1377–1404.

Burdett, Kenneth and Dale T. Mortensen (1998). “Wage Differentials, Employment Size, and Unemployment”. In: *International Economic Review* 39.2, pp. 257–273.

Caldwell, Sydnee and Oren Danieli (2023). “Outside options in the labor market”. In: *The Review of Economic Studies*. accepted.

Caliendo, Lorenzo, Maximiliano A. Dvorkin, and Fernando Parro (2019). “Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock”. In: *Econometrica* 87.3, pp. 714–835.

Card, David, Jörg Heining, and Patrick Kline (2013). “Workplace Heterogeneity and the Rise of West German Wage Inequality”. In: *Quarterly Journal of Economics* 128.3, pp. 967–1015.

Card, David, Jörg Heining, and Patrick Kline (2015). "CHK Effects". FDZ Methodenreport 6.

Card, David, Jesse Rothstein, and Moises Yi (2023). *Location, location, location.* Tech. rep. National Bureau of Economic Research.

Chernozhukov, V. and H. Hong (2003). "An MCMC Approach to Classical Estimation". In: *Journal of Econometrics* 115.2, pp. 293–346.

Combes, Pierre-Philippe, Gilles Duranton, and Laurent Gobillon (2008). "Spatial wage disparities: Sorting matters!" In: *Journal of Urban Economics* 63.2, pp. 723–742.

Datta, Nikhil (2022). "Local Monopsony Power". mimeo, University College London.

Dauth, Wolfgang, Sang Yoon Tim Lee, Sebastian Findeisen, and Tommaso Porzio (2021). "Transforming Institutions: Labor Reallocation and Wage Growth in a Reunified Germany". mimeo.

Eberle, Johanna, Peter Jacobebbinghaus, Johannes Ludsteck, and Julia Witter (2011). "Generation of Time-Consistent Industry Codes in the Face of Classification Changes - Simple Heuristic Based on the Establishment History Panel (BHP)". FDZ Methodenreport, 05/2011, Nuernberg.

Elsby, Michael WL and Axel Gottfries (2022). "Firm dynamics, on-the-job search, and labor market fluctuations". In: *The Review of Economic Studies* 89.3, pp. 1370–1419.

Engbom, Niklas (2020). "Misallocative Growth". mimeo.

Franzmann, Gabriele (2007). "Bevölkerung in der ehemaligen DDR 1946-1989". In: *GESIS Datenarchiv, Köln histat., Studiennummer 8267*.

Fuchs-Schündeln, Nicola, Dirk Krueger, and Mathias Sommer (2010). "Inequality Trends for Germany in the Last Two Decades: A Tale of Two Countries". In: *Review of Economic Dynamics* 13.1, pp. 103–132.

Galenianos, Manolis, Philipp Kircher, and Gabor Virag (2011). "Market power and efficiency in a search model". In: *International economic review* 52.1, pp. 85–103.

Gelman, Andrew, John B Carlin, Hal S Stern, David B Dunson, Aki Vehtari, and Donald B Rubin (2013). *Bayesian data analysis.* Chapman and Hall/CRC.

Gollin, Douglas, David Lagakos, and Michael E. Waugh (2014). "The Agricultural Productivity Gap". In: *Quarterly Journal of Economics* 129.2, pp. 939–993.

Henkel, Marcel, Tobias Seidel, and Jens Suedekum (2021). "Fiscal transfers in the spatial economy". In: *American Economic Journal: Economic Policy* 13.4, pp. 433–68.

Herrendorf, Berthold and Todd Schoellman (2018). "Wages, Human Capital, and Barriers to Structural Transformation". In: *American Economic Journal: Macroeconomics* 10.2, pp. 1–23.

Hethey-Maier, Tanja and Johannes F. Schmieder (2013). "Does the Use of Worker Flows Improve the Analysis of Establishment Turnover? Evidence from German Administrative Data". In: *Schmollers Jahrbuch: Journal of Applied Social Sciences* 133.4, pp. 477–510.

Hicks, Joan Hamory, Marieke Kleemans, Nicholas Y Li, and Edward Miguel (2017). "Reevaluating Agricultural Productivity Gaps with Longitudinal Microdata". In: *Journal of the European Economic Association* 19.3, pp. 1522–1555.

Hoffmann, Florian and Shouyong Shi (2016). "Burdett-Mortensen Model of On-the-Job-Search with Two Sectors". In: *Review of Economic Dynamics* 19, pp. 108–134.

Hsieh, Chang-Tai, Erik Hurst, Charles I Jones, and Peter J Klenow (2019). "The allocation of talent and us economic growth". In: *Econometrica* 87.5, pp. 1439–1474.

Hsieh, Chang-Tai and Peter J. Klenow (2009). "Misallocation and Manufacturing TFP in China and India". In: *Quarterly Journal of Economics* 124.4, pp. 1403–1448.

Jäger, Simon, Benjamin Schoefer, Samuel Young, and Josef Zweimüller (2020). "Wages and the Value of Nonemployment". In: *The Quarterly Journal of Economics* 135.4, pp. 1905–1963.

Jarosch, Gregor (2023). "Searching for Job Security and the Consequences of Job Loss". In: *Econometrica* 91.3, pp. 903–942.

Kennan, John and James R Walker (2011). "The effect of expected income on individual migration decisions". In: *Econometrica* 79.1, pp. 211–251.

Kline, Patrick, Raffaele Saggio, and Mikkel Sølvsten (2019). "It Ain't Where You're From, It's Where You're At.." In: Presented at the Models of Linked Employer-Employee Data Conference 2019.

Krueger, Alan B. and Jörn-Steffen Pischke (1995). "A Comparative Analysis of East and West German Labor Markets: Before and After Unification". In: *Differences and Changes in Wage Structures.* Ed. by Richard B. Freeman and Lawrence F. Katz. University of Chicago Press, pp. 405–446.

Lagakos, David, Samuel Marshall, Ahmed Mushfiq Mobarak, Corey Vernot, and Michael E Waugh (2020). "Migration costs and observational returns to migration in the developing world". In: *Journal of Monetary Economics.*

Le Barbanchon, Thomas, Roland Rathelot, and Alexandra Roulet (Oct. 2020). "Gender Differences in Job Search: Trading off Commute against Wage". In: *Quarterly Journal of Economics* 136.1, pp. 381–426. DOI: 10.1093/qje/qjaa033.

Lentz, Rasmus and Dale T Mortensen (2012). "Labor Market Friction, Firm Heterogeneity, and Aggregate Employment and Productivity". mimeo, University of Wisconsin.

Lindenlaub, Ilse, Ryungha Oh, and Michael Peters (2022). *Firm Sorting and Spatial Inequality.* Tech. rep. National Bureau of Economic Research.

Lise, Jeremy, Costas Meghir, and Jean-Marc Robin (2016). "Matching, sorting and wages". In: *Review of Economic Dynamics* 19, pp. 63–87.

Manning, Alan and Barbara Petrongolo (2017). "How local are labor markets? Evidence from a spatial job search model". In: *American Economic Review* 107.10, pp. 2877–2907.

Martellini, Paolo (2022). *Local labor markets and aggregate productivity.* Tech. rep. Working Paper.

Meghir, Costas, Renata Narita, and Jean-Marc Robin (2015). "Wages and informality in developing countries". In: *American Economic Review* 105.4, pp. 1509–46.

Melitz, Marc J (2003). "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity". In: *econometrica* 71.6, pp. 1695–1725.

Mortensen, Dale T. (2005). *Wage dispersion: why are similar workers paid differently?* MIT press.

Moscarini, Giuseppe and Fabien Postel-Vinay (2016). "Did the Job Ladder Fail after the Great Recession?" In: *Journal of Labor Economics* 34.S1, S55–S93.

Moser, Christian and Niklas Engbom (2022). "Earnings Inequality and the Minimum Wage: Evidence from Brazil". In: *American Economic Review* 112.12, pp. 3803–3847.

Paetzold, Jörg and Markus Tiefenbacher (2018). "Distributional and Revenue Effects of a Tax Shift from Labor to Property". In: *International Tax and Public Finance* 25.5, pp. 1215–1251.

Pavcnik, Nina (2002). "Trade liberalization, exit, and productivity improvements: Evidence from Chilean plants". In: *The Review of economic studies* 69.1, pp. 245–276.

Petrongolo, Barbara and Christopher A Pissarides (2001). "Looking into the black box: A survey of the matching function". In: *Journal of Economic literature* 39.2, pp. 390–431.

Pissarides, Christopher A (2000). *Equilibrium unemployment theory.* MIT press.

Roca, Jorge De La and Diego Puga (2017). "Learning by working in big cities". In: *The Review of Economic Studies* 84.1, pp. 106–142.

Schmutz, Benoît and Modibo Sidibé (2018). "Frictional Labour Mobility". In: *The Review of Economic Studies* 86.4, pp. 1779–1826.

Uhlig, Harald (2006). "Regional Labor Markets, Network Externalities, and Migration: The Case of German Reunification". In: *American Economic Review* 96.2, pp. 383–387.

— (2008). "The Slow Decline of East Germany". In: *Journal of Comparative Economics* 36.4, pp. 517–541.

Valentinyi, Akos and Berthold Herrendorf (2008). "Measuring factor income shares at the sectoral level". In: *Review of Economic Dynamics* 11.4, pp. 820–835.

Van Den Berg, Gerard J. and Geert Ridder (1998). "An Empirical Equilibrium Search Model of the Labor Market". In: *Econometrica* 66.5, pp. 1183–1221.

Online Appendix

A Further Details on Data and Data Construction

In this section, we discuss the main variables and data construction steps of the paper. We provide detail on other variables in Supplementary Appendix K.[64]

We use the Establishment History Panel (BHP) version 7514, covering the years 1975-2014. We use the longitudinal model of the Linked Employer-Employee Data (LIAB), version 9314, covering 1993-2014. IAB regulations do not allow us to merge these datasets. However, as part of the LIAB data, we obtain some variables from the BHP for those establishments that are matched to a worker in the LIAB.

BHP Data. The BHP is a 50% sample of all establishments in Germany with at least one employee subject to social security as of 30th of June of a given year. The data are reported as a panel dataset at the establishment-year level. As in the main text, we refer to establishments as "firms" going forward.

We obtain for each firm the location at the county level and the number of full-time workers, as well as the share of full-time workers by gender, education, and age. We create a dummy for whether a firm is in East Germany, and we code the dummy as missing if the firm is in Berlin. We obtain the mean gross daily wage paid to full-time employees by each firm in each year. Since the data contain earnings only up to the upper limit for earnings for statutory pension insurance contributions, approximately 10% of full-time employees' earnings are censored. To remedy this issue, the BHP provides a corrected mean gross daily wage for each firm, which we use for all our analyses. The imputation procedure follows Card et al. (2015). We use the time-consistent 3-digit industry codes at the WZ93 level for each firm. These time-consistent codes were constructed by Eberle et al. (2011) and are provided to us by the IAB.

We only keep our core period 2009-2014. This dataset contains 8.8 million firm-year observations. We drop firms with no full-time workers and remove firms located in Berlin, which reduces the sample size by 3.8 million and 200,000, respectively. We adjust the wages for cost of living differences and deflate them using county-specific price indices, described in more detail below. The final dataset contains 4,797,798 firm-year observations. We present some summary statistics in Supplementary Appendix K.

[64] This Supplemental Appendix is not meant for publication and includes additional material to provide context or robustness checks. It is available on the authors' websites.

LIAB Data. The LIAB data provide matched employer-employee data that link more than 1.9 million individuals to about 400,000 firms. The data contain information for the unemployment spells during which workers receive unemployment insurance benefits. Workers do not appear in the data if they are self-employed, in the public sector, or unemployed without receiving UI benefits.

The LIAB data report a new employment spell each time an individual's employment status changes, for example due to a change in job, wage, or employment status. Since our data provide the exact start and end date of each spell, time aggregation is not an issue. For employed workers, one spell is recorded in every calendar year even if there is no change in employment status. For unemployed workers the spell length may exceed one year. We split such long episodes into separate records so that each spell begins and ends in the same calendar year. About 10% of worker-start date-end date episodes are associated with multiple spells (7% if we exclude part-time work, which is our sample below). We replace partially overlapping employment spells with artificial observations with new dates so that completely parallel and completely non-overlapping periods are created. We keep only the worker's highest-paying job in cases of completely overlapping spells. This main job, on average, accounts for 81% of the worker's period income (median: 86%).

We obtain an individual's daily wage or unemployment benefit. As in the BHP, earnings are only reported up to the upper earnings limit for statutory pension insurance contributions. Since no imputed earnings variable is provided by the IAB, we perform our own imputation of the censored earnings, replicating the methodology described in Card et al. (2015).

We obtain each worker's county of residence, which is available since 1999, and for employed workers the county of their job. We set each individual's birth county as the earliest available county of residence or county of work recorded for the worker, from any record, including part-time or unemployed. If the earliest county of work and county of residence are from the same spell, we use the county of residence. We compute the distance between any county pair from Google maps, using the mid point of the counties.

We construct eight age dummies (26-30 years, 31-35 years, 36-40 years, 41-45 years, 46-50 years, 51-55 years, 56-60 years, older than 60 years), as well as a gender dummy and a dummy for whether the worker has a college education. The education variable is less than 85% complete for employed workers and unavailable for unemployed workers. We therefore set the dummy to zero if education is missing and include in our analyses an additional dummy to capture missing cases.

Our baseline analysis contains 15.1 million employment or unemployment spells for our baseline period 2009-2014. We drop part-time workers, which removes 5.0 million spells. We also remove 32,032 spells where the worker is employed abroad, and 9,666 spells where the residence county is missing. Finally, we also drop 657,487 observations where the worker is employed in Berlin. We adjust the wages for cost of living differences and deflate them using county-specific price indices, described in more detail below. The final dataset contains 9,485,701 observations. Supplementary Appendix K provides some summary statistics.

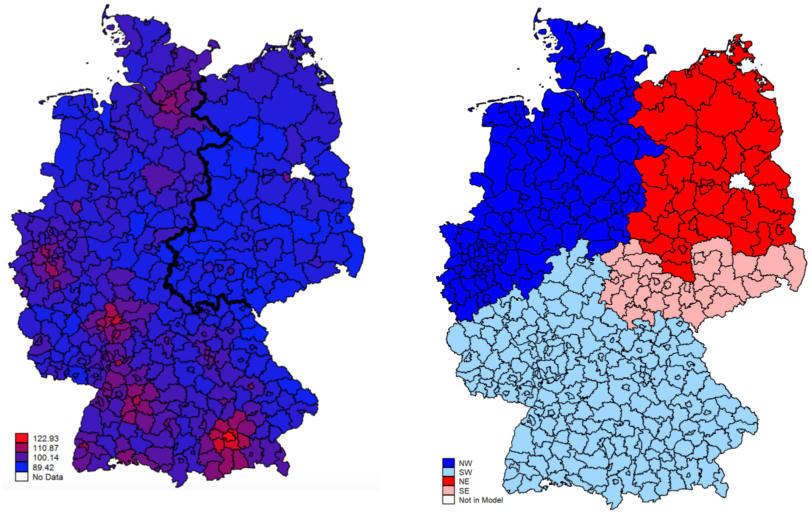
We obtain firm-level information from the matched BHP data for firms in which at least one worker in the LIAB has an employment spell. As in the BHP above, we keep only firms with at least one full-time worker, which reduces the number of firm observations from originally 2.4 million to 2.0 million. The matched sample contains about 40% of the firm-year observations of our BHP sample above. We present some summary statistics in Supplementary Appendix K. Due to the smaller size of the LIAB-BHP sample, we rely on the BHP sample to compute the firm-level moments we use in our model estimation.

Price Deflators. We obtain regional price data from a study of the Federal Institute for Building, Urban Affairs and Spatial Development (BBSR (2009)). The study computed prices in 2007 for 393 micro regions covering all of Germany that correspond to cities, counties, or slightly larger unions of counties. The data cover about two thirds of the consumption basket, including housing rents, food, durables, holidays, and utilities. Of the 402 counties in the IAB data, 311 are directly represented in the BBSR data. A further 81 counties in the IAB data can be mapped to 41 regions in the BBSR data that are slightly larger than a county or combine multiple counties. The remaining 10 counties in the IAB data are represented in the BBSR data by the main town within them. We obtain 2007 prices for each of the 402 counties in the IAB data (shown in Figure A1a), and then apply the price deflator of the corresponding state from the growth accounting of the states to each county to obtain a county-level price index for each year in 2009-2014.

Locations for the Quantitative Estimation. In the quantitative estimation of the model we divide Germany into four locations. Figure A1b visualizes the locations. In Supplemental Appendix K, we provide further summary statistics.

Figure A1: Price Level and Locations

(a) Price Level, 2007 (b) Locations in the Estimation



Source: BBSR, authors' calculations. Note: The left figure plots the price level in 2007 for each county, in euros valued in Bonn, the former capital of West Germany, from the BBSR (i.e., Bonn=100). The right figure presents the geography of the four locations used in the estimation.

B Statistics on Worker Mobility

Mobility Across Regions. We provide some additional statistics on worker mobility across regions. The top part of Table A1 presents the number of cross-region movers in our core sample for migrants, which, as defined in the main text, change their residence (column 1). We also show statistics for all job-to-job switchers across regions (column 2). We find that about 80% of cross-region job moves are done without a reported change in residence. We refer to such moves as "commuting". Since individuals may not list the residence closest to their job in the case of multiple residences, there may be mismeasurement in commuting. We therefore define a third, "intermediate" version of cross-region migration as all migration moves plus all cross-region job switches without a change in residence that take the worker further away from her current residence, as long as the work county is within 200km of the residence county both before and after the move. We impose this upper bound on distance to remove workers with implausibly long commutes. Moreover, we require the distance to the residence to increase since moves that decrease the distance do not really impose a moving cost on the worker.

The bottom panel of Table A1 shows percentiles of the distance between the origin and the destination job for cross-region job-to-job movers ("Work") and between the worker's new job and her residence after the move ("Live"). Workers move on average about 300km between jobs, with some job switchers moving more than 500km. Most workers live close to their job; however, some workers in the tail report distances to their residence of 400km or more. These workers likely have a misclassified residence county. We alleviate this issue somewhat with our intermediate definition.

Figure A2 presents the time series of the share of workers that is employed or unemployed away from their home region (circles) and the share of workers that are living away from home (triangles). We find that the share of individuals working and living away from their home region has leveled off, suggesting that population shares have arrived near a steady state.

Supplemental Appendix N contains additional statistics on the characteristics of migrants (analogous to Table 1). It also contains the distribution of moves throughout workers' life time and mobility by cohort.

Worker Mobility Across Locations. Table A2 presents statistics on worker mobility across the locations used in the quantitative estimation of the model. Similar to above, we distinguish between migrants, which change their residence location (column 1), all job-to-job switchers across locations (column 2), and an "intermediate version" of cross-location migration (column 3), which contains all migration moves plus all cross-location job switches without a change in residence that take the worker further away from her current residence, as long as the work county remains within 200km of the worker's residence county. We use this intermediate definition of a cross-location move in our estimation in Section 5.

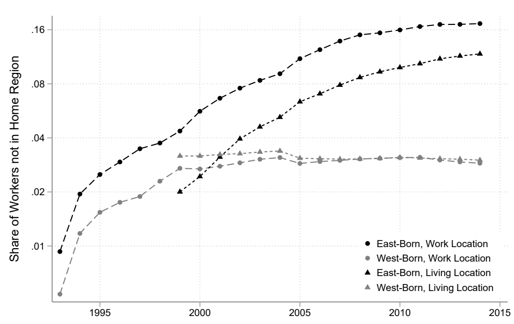
Table A1: Number of Movers Between East and West Germany

	Migration	All Cross-Region	Intermediate
Number of movers	13,853	59,603	21,199
- East-to-West	7,919	31,673	13,350
- West-to-East	5,934	27,930	7,849
Avg. moves per year	0.003	0.010	0.004

	Migration		All Cross-Region		Intermediate	
Distance	Work	To Live	Work	To Live	Work	To Live
Mean	305.054	72.498	277.848	136.381	233.558	79.956
P5	73.258	0	36.662	0	28.532	0
P50	308.840	5.661	289.260	48.387	210.635	35.203
P95	530.993	389.323	510.573	463.083	499.491	339.766

Source: LIAB. Notes: The first column of the top panel considers job-to-job migration moves (i.e., the worker changes her residence region in the same year), the second column contains all job-to-job switches between East and West, i.e., migrants plus commuters, and the third column considers migration moves plus other cross-region moves that increase the distance to the residence county, as long as the distance to the residence county does not exceed 200km, as described in the text. All figures are for our sample period 2009-2014. The first three rows of the top panel show the number of cross-region movers between East and West overall, East-to-West, and West-to-East, respectively. The fourth row computes for each worker the average number of moves between East and West divided by the number of years the worker is in the data, and averages across all workers. The bottom panel presents some statistics on the distance of moves. The "Work" columns show the average distance between the county of the origin job and the county of the destination job for cross-region movers, as well as some selected moments of the distribution. The "To Live" present similar statistics for the distance between the work and the residence county of the worker at the destination job for cross-region movers.

Figure A2: Stock of Individuals Away from Home Region



Source: LIAB. Notes: The circles plot the share of workers of a given type that are working or receiving unemployment benefits in their non-home region, for East Germans (black) and West Germans (gray). Each worker is counted once per year and region, regardless of the number of spells in that region. The triangles analogously plot the share of workers reporting their residence in their non-home region.

Table A2: Number of Movers Between Locations

	Migration	All Cross-Loc	Intermediate
Number of movers	31,676	133,166	49,117
Avg. moves per year	0.006	0.022	0.009

	Migration		All Cross-Loc		Intermediate	
Distance	Work	To Live	Work	To Live	Work	To Live
Mean	322.965	81.403	292.468	144.370	244.471	87.475
P5	70.578	0	36.949	0	31.311	0
P50	323.308	14.526	295.398	49.985	199.700	38.770
P95	588.087	425.205	588.158	496.733	545.368	367.116

Source: LIAB. Notes: The first column of the top panel considers job-to-job migration moves between locations (i.e., the worker changes her residence location in the same year), the second column contains all job-to-job switches between locations, i.e., migrants plus commuters, and the third column considers migration moves plus other cross-location moves that increase the distance to the residence county, as long as the distance to the residence county does not exceed 200km, as described in the text. All figures are for our sample period 2009-2014. The first row of the top panel shows the number of cross-region movers between locations. The second row computes for each worker the average number of moves between locations divided by the number of years the worker is in the data and averages across all workers. The bottom panel presents some statistics on the distance of moves. The "Work" columns show the average distance between the county of the origin job and the county of the destination job for cross-location movers, as well as some selected moments of the distribution. The "To Live" present similar statistics for the distance between the work and the residence county of the worker at the destination job for cross-location movers.

C Results from the Socio-Economic Panel

We use survey data from the German Socio-Economic Panel (SOEP) to examine how accurately our imputed home region in the LIAB reflects the individual's true birth region. The SOEP data consist of samples drawn in different "waves", and a reliable measure of birth region is available for two of them. First, the wave of individuals in the SOEP drawn in 1984 covered only West German individuals, while a wave in 1990 covered only East German individuals, identifying the birth region with certainty. We will refer to individuals from these waves that are still in the labor force in 2009-2014 as the "Old SOEP Sample". Second, for individuals that entered the survey while they were still in their childhood, we use information on the individuals' schooling. We code the home region as the location of the individual's earliest observed non-tertiary schooling. We refer to individuals where we have this information as the "Young SOEP Sample". While the SOEP also asks some individuals about their place of residence in 1989, that variable is only available for about 0.5% of individual-year observations.

We construct an imputed home region in the same way and subject to the same restrictions as in the LIAB. Table A3 compares the imputed and actual home region for individuals that are in the labor force in 2009-2014. We find that in both samples the imputed and the actual home region match closely.

Table A3: Fraction of Individuals Where Imputed Home Region Matches Actual

	Old SOEP Sample		New SOEP Sample	
	East	West	East	West
	(1)	(2)	(3)	(4)
Imputed = Actual	.8752	.9891	.9200	.9923
Observations	769	1,285	350	1,306

Notes: We compute in the SOEP an imputed home region in the same way as in the LIAB. Specifically, we use only SOEP data from 1993 onward, exclude Berlin, and drop residence information prior to 1999. We then use the worker's region of residence at the first time he/she is observed in employment or unemployed, but not outside of the labor force, from 1999 onwards, or the worker's job region prior to 1999, to assign an imputed home region. We compare this imputed home region to the actual birth region based on the SOEP for individuals that are either employed or unemployed in 2009-2014. The birth region is known perfectly in the Old SOEP Sample. In the New SOEP Sample, it is equal to the region in which the individual was located at the earliest schooling for which we have data (prior to tertiary education). The figures show the proportion of observations for which the two match.

As a more rigorous test, we compare the wage gap between individuals classified as East and West German under our imputation to the wage gap calculated with the true birth/schooling region. Given the limited data, we extend the period to 2004-2014, and run for employed workers the regression

$$\log(w_{it}) = \gamma \mathbb{I}_{i,East,r} + \beta X_{it} + \delta_t + \epsilon_{it},$$

where w_{it} is worker i's wage in year t and $\mathbb{I}_{i,East,r}$ is a dummy for the worker's home region, with either the true home location ($r = true$) or the imputed location ($r = imp$). The controls X_{it} contain a dummy for the worker's gender, two dummies for age (30-49 years and 50+ years), two dummies for school – i) Realschule or technical school; ii) Gymnasium or equivalent – and two dummies for post-secondary education, indicating i) at most a vocational degree; ii) a college degree.

Table A4 shows the results. The wage gap is similar under both the true and the imputed region definitions. Thus, we find no evidence that our misclassification of some workers quantitatively alters the wage gap. Given this evidence, we also interpret workers' home region as their "birth" region.

Table A4: Individual-Level Wages by Imputed Home Region versus Birth Region in the SOEP

	Old SOEP Sample				New SOEP Sample			
$\log(w_{it})$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{I}_{i,East,imp}$	$\mathbf{-.346}^{***}$	$\mathbf{-.404}^{***}$			$\mathbf{-.160}^{***}$	$\mathbf{-.163}^{***}$		
	(.0212)	(.0196)			(.0325)	(.0309)		
$\mathbb{I}_{i,East,true}$			$\mathbf{-.338}^{***}$	$\mathbf{-.406}^{***}$			$\mathbf{-.133}^{***}$	$\mathbf{-.127}^{***}$
			(.0207)	(.0192)			(.0319)	(.0303)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Age/edu/male	–	Y	–	Y	–	Y	–	Y
Observations	15, 240	15, 210	15.240	15, 210	2, 894	2, 540	2, 894	2, 540

Notes: $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the individual level. $\mathbb{I}_{i,East,imp}$ is a dummy for the worker's home region, which is imputed using the same procedure as in the LIAB. The dummy is equal to one if the worker's home region is East Germany. $\mathbb{I}_{i,East,true}$ is a dummy for a worker's birth region (Old SOEP sample) or region of earliest non-tertiary schooling (Young SOEP sample) as read off from the SOEP survey. The sample period is 2004-2014. Male is a dummy that is equal to one if the worker is male. Age are two dummies for 30-49 years and for 50+ years. Edu are two dummies for school: i) Realschule or technical school; ii) Gymnasium or equivalent; and two dummies for post-secondary education: indicating i) at most a vocational degree; ii) a college degree.

D Proofs and Additional Formulas

D.1 Equilibrium in the Goods Market

The firm's problem in the goods market is

$$\hat{\pi}_j(w) = \max_{n_h, n_c, k} \left\{ pn_c + P_{h,j} \left(pn_h \right)^{1-\alpha} k^{\alpha} - \rho_j k \right\} \tag{23}$$

subject to $n_c + n_h = n_j(w)$. The first-order conditions of this problem imply

$$n_h = \frac{\rho_j}{p} \frac{1-\alpha}{\alpha} k \tag{24}$$

and assuming that both goods are supplied in equilibrium

$$P_{h,j} = \rho_j^{\alpha} \alpha^{-\alpha} \left(1-\alpha\right)^{-(1-\alpha)}. \tag{25}$$

We can plug (24) and (25) into (23) to obtain

$$\hat{\pi}_j(w) = pn_j(w) = p \sum_{i \in \mathbb{I}} \theta_j^i l_j^i(w), \tag{26}$$

where capital and labor demand for the local good have been maximized out.

The equilibrium price of the local good is determined from consumers' demand and market clearing. Due to the Cobb-Douglas utility, the aggregate demand for the local good H_j satisfies

$$P_{h,j}H_j = (1-\eta)\,P_jY_j, \tag{27}$$

where, assuming that consumers own the firms and using (26), their total income is

$$P_jY_j = \int z\left(\sum_{i\in\mathbb{I}}\theta_j^i l_j^i\,(w(z))\right)v_j\,(z)\,dz + \rho_j K_j$$

and Y_j is real GDP.

Using the production function $h = (pn_h)^{1-\alpha}k^{\alpha}$, and plugging in (24), aggregate supply of the local good in location j is $H_j = (\rho_j\frac{1-\alpha}{\alpha})^{1-\alpha}K_j$, which, using the price of the local good (25), implies

$$P_{h,j}H_j \quad = \quad \frac{1}{\alpha}\rho_jK_j. \tag{28}$$

Combining demand and supply yields

$$\frac{1}{\alpha}\rho_jK_j = (1-\eta)\left\{\int p\left(\sum_{i\in\mathbb{I}}\theta_j^i l_j^i\,(w(z))\right)v_j\,(z)\,dz + \rho_jK_j\right\}.$$

Given wages and the fixed K_j, this equation pins down the equilibrium price ρ_j, which in turn determines the local price P_j.

We can express the equilibrium condition in terms of ratios as follows. Starting from $P_j = (P_{h,j})^{1-\eta}$, we can substitute in with (25) and use the supply equation (28) to obtain

$$\frac{P_j}{P_x} = \left(\frac{P_{h,j}H_j}{P_{h,x}H_x}\right)^{\alpha(1-\eta)}\left(\frac{K_j}{K_x}\right)^{-\alpha(1-\eta)}.$$

Combining this expression with the demand equation (27) gives

$$\frac{P_j}{P_x} = \left(\frac{P_jY_j}{P_xY_x}\right)^{\alpha(1-\eta)}\left(\frac{K_j}{K_x}\right)^{-\alpha(1-\eta)},$$

as claimed in the main text.

D.2 Additional Formulas

The probability that a worker of type i employed at wage w in region j accepts an offer w' from region x is

$$\mu_{jx}^{E,i}\left(w,w'\right) \equiv \frac{\exp\left(W_x^i\left(w'\right)-\kappa_{jx}^i\right)^{\frac{1}{\sigma}}}{\exp\left(W_j^i\left(w\right)\right)^{\frac{1}{\sigma}}+\exp\left(W_x^i\left(w'\right)-\kappa_{jx}^i\right)^{\frac{1}{\sigma}}}$$

The corresponding probability for an unemployed worker is

$$\mu_{jx}^{U,i}\left(b_j^i,w'\right) \equiv \frac{\exp\left(W_x^i\left(w'\right)-\kappa_{jx}^i\right)^{\frac{1}{\sigma}}}{\exp\left(U_j^i\right)^{\frac{1}{\sigma}}+\exp\left(W_x^i\left(w'\right)-\kappa_{jx}^i\right)^{\frac{1}{\sigma}}}.$$

D.3 Proof of Proposition 1

Firms choose the wage that maximizes profit per vacancy: they solve

$$\pi_j\left(p\right)=\max_w\left(p-w\right)\sum_{i\in\mathbb{I}}\theta_j^i l_j^i\left(w\right) \tag{29}$$

and, as shown in equation (17),

$$l_j^i\left(w\right)=\frac{\mathcal{P}_j^i\left(w\right)\vartheta_j^{-\chi\frac{\bar{a}_j^i}{\bar{a}_j}}}{q_j^i\left(w\right)} \quad \text{if } w\geq R_j^i \tag{30}$$

which embeds the optimal behavior of workers, as described in Mortensen (2005).

The proof is constructive and it shows that firm optimality leads to the system of differential equations described. The proof relies on the insights and results of the classic Burdett-Mortensen framework, but it refines them to accommodate for multiple locations and multiple worker types.

If the function $\pi_j\left(p,w\right)$ is continuous in w for a given p, then we can take the first order condition of problem (29) and obtain

$$\frac{\left(p-w_j\left(p\right)\right)\left(\sum_{i\in\mathbb{I}}\theta_j^i\frac{\partial l_j^i\left(w_j\left(p\right)\right)}{\partial w}\right)}{\left(\sum_{i\in\mathbb{I}}\theta_j^i l_j^i\left(w_j\left(p\right)\right)\right)} = 1. \tag{31}$$

From equation (30), we find

$$\frac{\partial l_j^i(w)}{\partial w} = \frac{\frac{\partial \mathcal{P}_j^i(w)}{\partial w} q_j^i(w) - \mathcal{P}_j^i(w)\frac{\partial q_j^i(w)}{\partial w}}{q_j^i(w)^2} \vartheta_j^{-\chi} \frac{\bar{a}_j^i}{\bar{a}_j}.$$

We then define the functions in terms of p, i.e., $\tilde{x}(p) \equiv x(w(p))$ for any x, so that

$$\begin{aligned} \frac{\partial \tilde{q}_j^i(p)}{\partial p} &= \left(\frac{\partial q_j^i(w)}{\partial w}\right)\left(\frac{\partial w_j(p)}{\partial p}\right) \\ \frac{\partial \tilde{\mathcal{P}}_j^i(p)}{\partial p} &= \left(\frac{\partial \mathcal{P}_j^i(w)}{\partial w}\right)\left(\frac{\partial w_j(p)}{\partial p}\right). \end{aligned}$$

Next, we replace these equations into the above equation for $\frac{\partial l_j^i(w)}{\partial w}$ to get

$$\frac{\partial l_j^i(w)}{\partial w} = \frac{\left(\frac{\partial w_j(p)}{\partial p}\right)^{-1}}{\tilde{q}_j^i(p)^2}\left(\frac{\partial \tilde{\mathcal{P}}_j^i(p)}{\partial p}\tilde{q}_j^i(p) - \tilde{\mathcal{P}}_j^i(p)\frac{\partial \tilde{q}_j^i(p)}{\partial p}\right)\vartheta_j^{-\chi}\frac{\bar{a}_j^i}{\bar{a}_j},$$

which can itself be substituted into (31) to find a differential equation for $w_j(p)$

$$\frac{\partial w_j(p)}{\partial p} = \frac{(p - w_j(p))\left(\sum_{i\in\mathbb{I}}\theta_j^i \frac{\frac{\partial \tilde{\mathcal{P}}_j^i(p)}{\partial p}\tilde{q}_j^i(p) - \tilde{\mathcal{P}}_j^i(p)\frac{\partial \tilde{q}_j^i(p)}{\partial p}}{\tilde{q}_j^i(p)^2}\vartheta_j^{-\chi}\frac{\bar{a}_j^i}{\bar{a}_j}\right)}{\left(\sum_{i\in\mathbb{I}}\theta_j^i \frac{\tilde{\mathcal{P}}_j^i(p)}{\tilde{q}_j^i(p)}\vartheta_j^{-\chi}\frac{\bar{a}_j^i}{\bar{a}_j}\right)}. \tag{32}$$

Since $w_j(p)$ is continuous at p by assumption, the differential equation (32), together with an appropriate boundary conditions, characterizes the optimal wage at p. Since workers can always voluntarily separate into unemployment while keeping their preference shocks, they must be paid at least $w = R_j^i$. Therefore, the boundary conditions are given by

$$w_j(\varphi_j) = \max\left\{\min_{i\in\mathbb{I}} R_j^i, \arg\max_{\hat{w}} (\varphi_j - \hat{w})\sum_{i\in\mathbb{I}}\theta_j^i l_j^i(\hat{w})\right\}.$$

We have thus proved that

$$w_j(p) = w_j(\varphi_j) + \int_{\varphi_j}^{p} \frac{\partial w_j(z)}{\partial z}\gamma_j(z)\,dz \tag{33}$$

as claimed.

E Parameters and Empirical Moments

We describe how the parameters and targeted moments are computed. We provide extensive details in Supplemental Appendix Q.

Calibrated Parameters

We estimate workers' skills θ^i from an AKM model with comparative advantage term, building on Abowd et al. (1999) and Card et al. (2013). We estimate in the LIAB data the following model with two regions, East and West Germany:

$$\log(w_{it}) = \alpha_i + \psi_{J(i,t)} + \beta \mathbb{I}^{(h_i \neq R(J(i,t)))} + BX_{it} + \epsilon_{it}, \tag{34}$$

where i indexes full-time workers, t indexes time, and $J(i,t)$ indexes worker i's firm at time t.[65] In this specification, α_i is the worker component, $\psi_{J(i,t)}$ is the component of the firm j for which worker i works at time t, and $\mathbb{I}^{(h_i \neq R(J(i,t)))}$ is a dummy that is equal to one if worker i with home region h_i (either East or West Germany) is currently employed at a firm in the other region. This term picks up the comparative advantage of workers in their home region. Finally, X_{it} is a centered cubic in age and an interaction of age and college degree, as in Card et al. (2013). We discuss the identification of this model in the dedicated appendix F below.

We specify, again following Card et al. (2013), ϵ_{it} as three separate random effects: a match component $\eta_{iJ(i,t)}$, a unit root ζ_{it}, and a transitory error ϵ_{it},

$$\epsilon_{it} = \eta_{iJ(i,t)} + \zeta_{it} + \epsilon_{it}.$$

We estimate the model on the largest connected set of workers in our data.[66]

The estimation yields a comparative advantage estimate of $\beta = 0.019$, indicating a small *negative* comparative advantage towards the home region. Given the lack of comparative advantage at the regional level where we would expect to find the largest effect, we do not extend the analysis to the level of the four finer locations we use in the estimation in

[65] Time is a continuous variable, since, if a worker changes multiple firms within the same year, we would have more than one wage observation within the same year.

[66] While most workers (97%) are included in the sample, we miss approximately 10% of the firms included in the LIAB dataset with at least one worker during 2009-2014 in East and 11% in the West. We are more likely to miss firms that pay lower wages. In fact, of the firms in the bottom decile of the average wage distribution we miss 19% in the East and 21% in the West, while of the firms in the top decile we miss 7% in the East and 5% in the West. We miss more firms than workers since large firms are more likely to be included in the connected set.

Section 5. However, the same insights and identification strategy would apply and could be performed. Since the presence of the premium would require the remaining frictions to be larger to rationalize the lack of East-to-West mobility, we conservatively set the comparative advantage to zero in our estimation. We obtain workers' absolute advantage from the average worker fixed effect for each worker type, see Supplemental Appendix Q.1.

Table A5 contains a brief discussion of the remaining parameters.

Table A5: Calibrated Parameters

	Parameter	Computed from...
(2)	M_j : Firms by location	Number of firm-year observations in the BHP
(3)	$\bar{D}^i$: Workers' home location	Population residing in each location in January 1991 from the Growth Accounting of the States
(4)	δ_j : Separation rate by location	Workers' monthly probability of separating into unemployment or permanent non-employment from LIAB
(5)	P_j : Price level by location	Weighted average of state-level price indices from BBSR
(6)	$\alpha(1-\eta)$: Pay to fixed factors	Interpret fixed factor as land, use share of land in GDP for the U.S. from Valentinyi and Herrendorf (2008)
(7)	χ : Matching elasticity	Assume CRS, set by assumption.
(8)	r : Interest rate	Assume infinitely lived individuals, set by assumption.

Notes: This table provides a brief summary how each calibrated parameter is computed. Details are in Supplemental Appendix Q.

Moments for the Estimation

Unless otherwise mentioned, all moments are constructed using the cleaned data described in the data section of the main text, for the core sample period 2009-2014. We briefly summarize the construction of the moments in Table A6, and delegate details to Supplemental Appendix Q.2.

F Identification of Workers' Skills

We now discuss how the specification (34) allows us to identify, through β, the comparative advantage effect by region. The same idea extends to more locations.

Consider four wage observations associated with two workers: an East-born and a West-born individual working in one firm in the East, and the same two individuals working in one firm

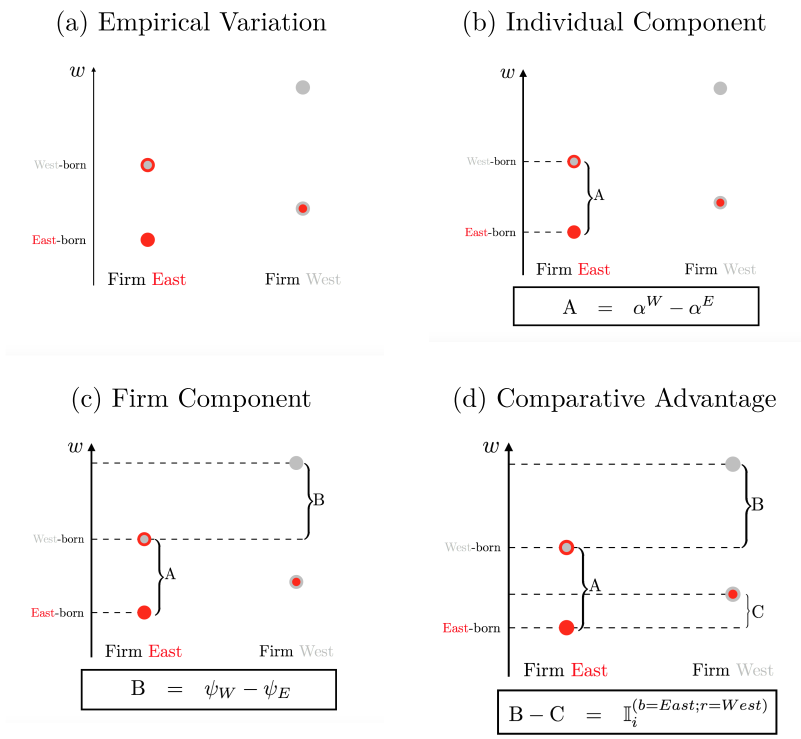
Table A6: Targeted Moments

	Parameter	Computed from...
(1)+(2)	Wage gains w/i + b/w locations	Regression in LIAB of movers' wage gains on dummies for moves w/i and b/w locations and conrols.
(3)+(4)	Job flows w/i + b/w locations	Monthly worker flows w/i and b/w locations from LIAB.
(5)+(6)	(Un)employment shares	Share of (un)employed workers living in each location in LIAB.
(7)	Average AKM firm fixed effect by worker location and type	Regression of AKM firm fixed effects on worker location and home location dummies
(8)	AKM firm fixed effects by firm location	Regression of AKM firm fixed effects on firm location dummies
(9)+(10)	Output p.c. and unemployment	National Accounts of the States and official unemployment statistics
(11)	Deciles of firm-size distribution	Share of workers employed at each firm size decile from BHP, with firm size residualized by age, education, gender, industry.
(12)	Slope of wage vs firm size	Coefficient of regression of firms' (residualized) average wage on (residualized) firm size from BHP.
(13)	Slope of J2J wage gain vs wage	Coefficient of regression of workers' (residualized) job-job wage gain on their (residualized) initial wage in LIAB.
(14)	Slope of separation rate vs firm wage	Coefficient of regression of (residualized) dummy for worker separation on their (residualized) initial wage in LIAB.
(15)	Std of wage gains of movers	Std of (residualized) wage gains of job movers in LIAB.
(16)	Profits to labor cost ratio	Pre-tax profits divided by total labor costs from ORBIS.

Notes: Table provides a summary of how each moment is computed. Details are in Supplemental Appendix Q.

in the West. Figure A3a plots an example of these two workers' wages, where the x-axis is the identity of the firm, the y-axis is the level of the wage, the inside coloring refers to the birth region of the worker, and the outside coloring refers to the region of the firm. Figures A3b-A3d then show how these data identify the three AKM components. First, as depicted in Figure A3b, the individual components are identified from comparing the wages of the two workers when employed at the same firm. If a worker at a given firm earns a higher wage, she is identified as having a higher individual component. Second, Figure A3c highlights that the firm components are identified by comparing the same worker at two different firms. If the worker earns a higher wage at firm X than at firm Y, this difference is attributed to a higher firm component of X. Finally, Figure A3d illustrates how the comparative advantage is identified. In the absence of comparative advantages, the two workers should have an identical wage gap between them in both firms. We can thus identify the comparative advantage by comparing the wage differentials between the two workers when employed in the East- and in the West-firm, respectively.

Figure A3: Identification of the AKM Components



Note: The figure illustrates the wage of two workers at two firms in East and West Germany, respectively, indexed on the x-axis. Inner coloring indicates the birth region of the worker (gray=West, red=East). Outer coloring indicates the region in which the firm is located.

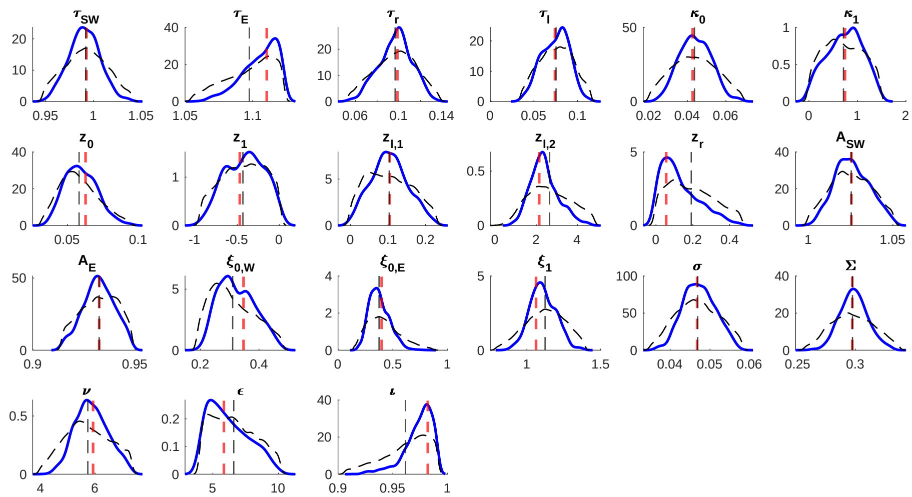
Note that the methodology cannot separately identify whether it is the East or the West-born worker that has a comparative (dis)advantage since all that is observed is their relative wage gap. As a result, the estimated β captures the sum of the two comparative advantages and we need to make an assumption in order to separately identify the two. In practice, we side-step this issue since we do not find evidence of comparative advantages as described above.

G Model's Computation and Estimation

We here provide a brief explanation of the solution algorithm and more details on the estimation approach and outcomes. Additional details, with a complete description of the solution and estimation algorithm are found in Supplemental Appendix S.

Computation. To solve the model, we follow a nested iterative procedure which leverages Proposition 1 to solve the model in the one-dimensional productivity space. For the counterfactuals, we follow the same algorithm, but keep the unemployment benefit constant

Figure A4: Estimation Outcomes



Notes: The figure shows the outcomes of the estimation. Each panel shows a different one of the 21 estimated parameters. As described in the text, the black dashed and blue lines show the densities for different sub-sets of parameter draws. The red vertical lines are our estimated parameters, while the black vertical lines show the estimates that we would obtain with the alternative approach, described above. The top row shows the estimation results for τ_{SW}, τ_E, τ_r, τ_l, κ_0 and κ_1. The second row shows the results for z_0, z_1, $z_{l,1}$, $z_{l,2}$, z_r, and A_{SW}. The third row shows the estimates for A_E, $\xi_{0,W}$, $\xi_{0,E}$, ξ_1, σ, and Σ. The last row shows the estimates for ν, ϵ, and ι.

(rather than estimating it to match the reservation wage), and allow equilibrium prices to respond to local GDP (rather than simply using their empirical values, which we do in the estimation).

Estimation. The objective is to find a parameter vector ϕ^* that solves

$$\phi^* \quad = \quad \arg\min_{\phi \in \mathbb{F}} \sum_x \left[\omega_x \left(T_x \left(m_x \left(\phi \right), \hat{m}_x \right) \right)^2 \right] \tag{35}$$

and $\mathbb{F}$ is the set of admissible parameter vectors. The choice of the function $T_x(\cdot)$ minimizes either the sum of the percentage deviations between model-generated and empirical moments or log differences, as explained in the Supplemental Appendix S. We introduce a weighting factor ω_x to give equal weight to each one of the 16 groups of parameters that we target, shown in Table 4.

We then use a fairly standard simulation-based minimization routine to solve the minimization problem. Figure A4 illustrates our approach and how it slightly differs from others such as Jarosch (2023) and Lise et al. (2016). The black dotted line shows the density function of the last 1,000 iterations across all strings. The usual approach is to pick the average across all these draws, which we highlight in the picture with a vertical black dotted line. We instead pick the parameters following Moser and Engbom (2022), and thus select the vector

Table A7: All Estimated Parameters

(1)	τ_{SW}: amenity SW	0.993	(12)	A_{SW}: productivity SW	1.025
(2)	τ_E: amenity East	1.110	(13)	A_E: productivity East	0.932
(3)	τ_r: region preference	0.099	(14)	$\xi_{0,W}$: vacancy cost West	0.347
(4)	τ_l: location preference	0.074	(15)	$\xi_{0,E}$: vacancy cost East	0.398
(5)	κ_0: move cost out of location	0.043	(16)	ξ_1: vacancy curvature	1.062
(6)	κ_1: move cost distance	0.742	(17)	σ: variance of taste shocks	0.047
(7)	z_0: search out of location	0.063	(18)	Σ: variance p distribution	0.297
(8)	z_1: search distance	-0.469	(19)	ν: search intensity of unemployed	5.926
(9)	$z_{l,1}$: search in home location	0.105	(20)	ϵ: curvature search cost	5.841
(10)	$z_{l,2}$: search to home location	2.146	(21)	ι: workers' outside option	0.982
(11)	z_r: search to home region	0.055			

Notes: The table reports the 21 parameters estimated from our model, estimated according to the procedure described above.

of parameters that minimizes the objective function among all our draws. Our estimates are shown with red dotted lines in the figure. For most parameters, they are almost identical to the alternative approach. Finally, the blue density functions show the density, across all strings, of the 10 best outcomes within each string. This density provides a visual representation of the tightness of our estimates, which are, in general, quite good – especially for the key parameters that determine the spatial frictions. It is also relevant to notice that all the densities are single-peaked, which suggests that the model is, at least locally, tightly identified.

All the estimated parameters, corresponding to the vertical dotted red lines, are included in Table A7.

Jacobian Matrix and Identification. To formally explore the connection between parameters and moments, we compute the elasticity of each (model-generated) moment to each model parameter.

Specifically, we start from the estimated vector of parameters ϕ^*, and we create 42 alternative vectors, two for each parameter j, as follows: $\underline{\phi}(j) = \left\{\phi^*_{-j}, 0.95\phi^*_j\right\}$ and $\overline{\phi}(j) = \left\{\phi^*_{-j}, 1.05\phi^*_j\right\}$, where $\underline{\phi}(j)$ keeps all parameters except for j constant and decreases j by 5%, while $\overline{\phi}(j)$ does the same, but increasing j by 5%.

We then compute with our model the vectors of moments corresponding to each vector of parameters and use them to compute

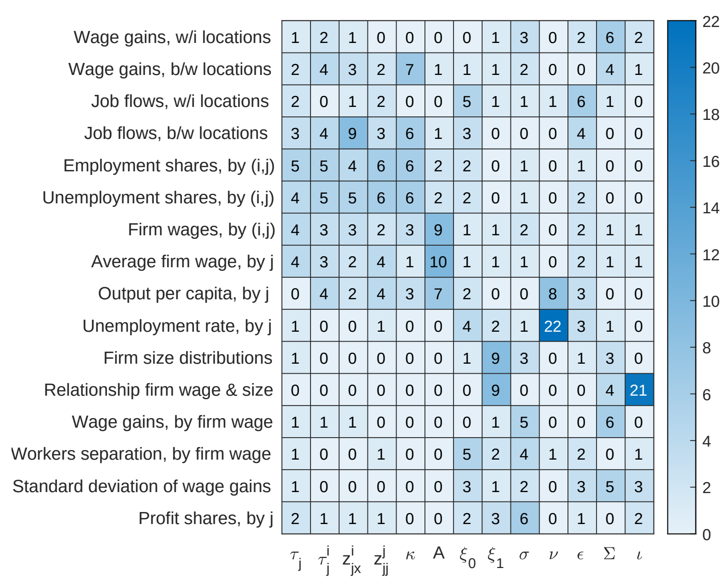
$$\Delta_{jr} = m_r\left(\overline{\phi}(j)\right) - m_r\left(\underline{\phi}(j)\right).$$

Thus, Δ_{jr} measures how much moment r would change if we changed parameter j by 10% around the estimated value while keeping all the other parameters constant.

Overall, we have 305 moments and 21 parameters, which would create a matrix with 6,405 cells; hence, impossible to read. Therefore, for the exposition we reduce the dimensionality by taking averages by groups of moments and parameters that are similar. Specifically, for the moments, we follow Table 4, and compute the averages by the 16 blocks shown there. For the parameters, we bundle together the following: i. the two relative amenities τ_{SW} and τ_E (referred to as τ_j in Figure A5); ii. the two home biases τ_l and τ_r $\left(\tau_j^i\right)$; iii. the relative search efficiencies between regions z_0, z_1, $z_{l,2}$ and z_r $\left(z_{jx}^i\right)$; iv. the cost of moving κ_0 and κ_1 (κ); v. the two relative productivities A_{SW} and A_E (A); vi. the two costs of vacancy posting $\xi_{0,W}$ and $\xi_{0,E}$ (ξ_0). In this way, we reduce the number of parameters to be shown to 13.

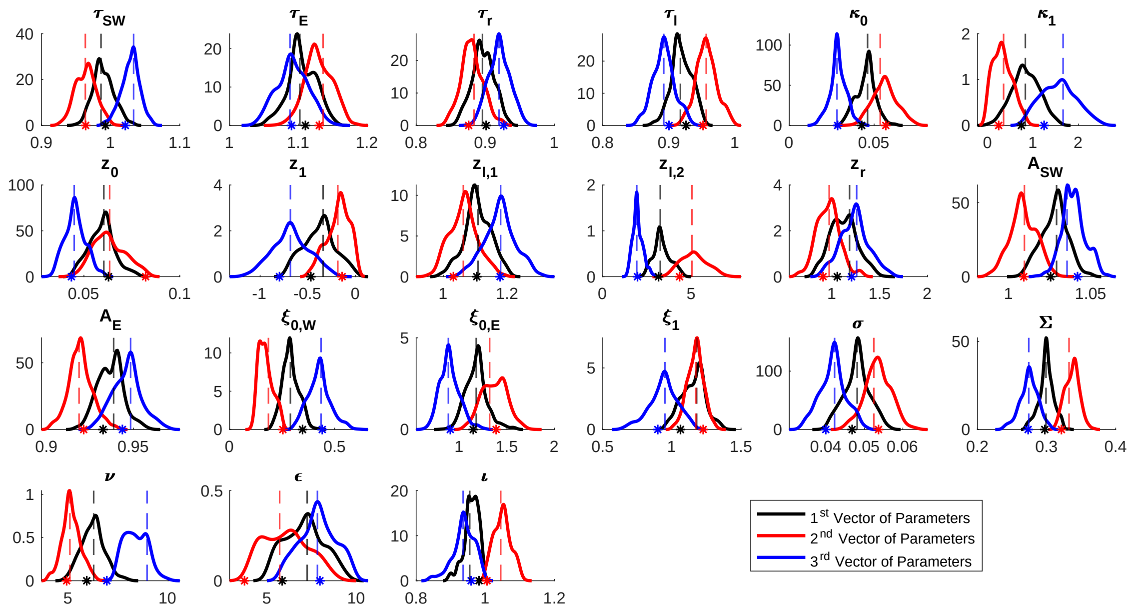
To ease comparison, we normalize Δ_{jr} for each parameter j so that, when rounded, it sums to 32 across all moments: $\sum_r Round\left(\Delta_{jr}\right) = 32$, i.e., twice the number of moment blocks. The result of this procedure is the Jacobian matrix shown in Figure A5, which illustrates which parameter is most important for each moment. Our normalization helps to generate interpretable magnitudes: if all moments are impacted in the same way by a specific parameter, then we should see a value of 2 for each parameter in the corresponding row; if only four moments are impacted by a parameter, with equal relevance, then we should see a value 8 for those moments and 0 otherwise, and so on.

Figure A5: Normalized Partial Derivatives of Moments with Respect to Parameters



Notes: The matrix includes the normalized values of Δ_{jr} computed as described in the text. Each row is a block of moments and each column represent one or more parameters.

Figure A6: Testing the Estimation Procedure

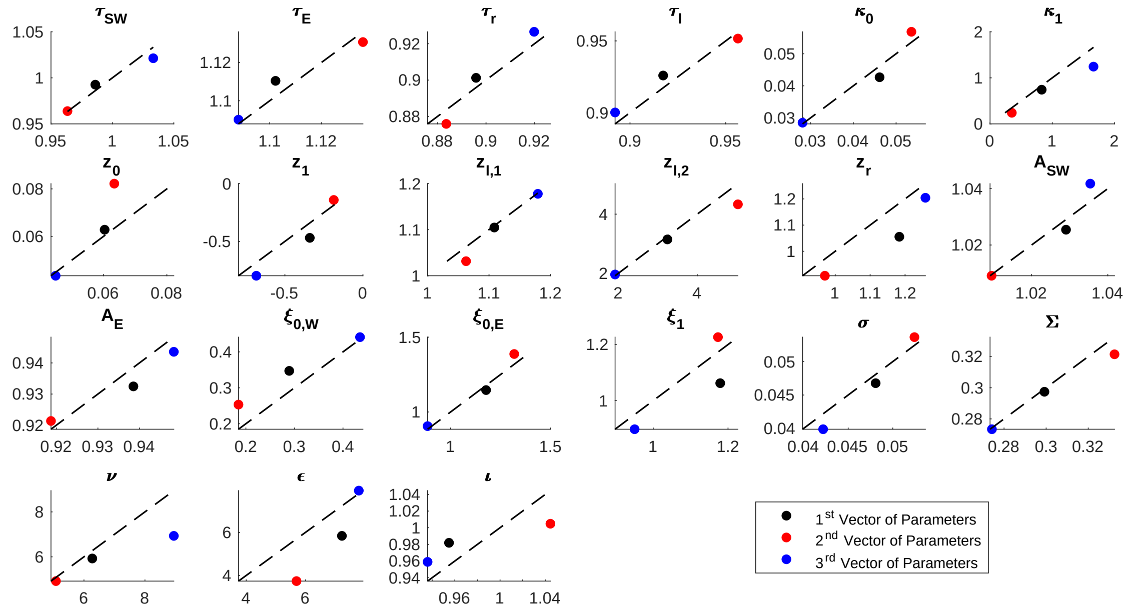


Notes: The figure compares the outcomes of the three estimations. Each panel shows a different one of the 21 estimated parameters. The stars on the x-axis show the true parameters, in black for the benchmark parameters, in blue and red for the two (random) alternative vectors. The solid lines show the densities of the best draws for each estimation string: they provide a visual representation of the tightness of our estimates. The vertical dashed lines show the final estimates.

Testing the Estimation Routine. To test the effectiveness of our estimation routine, we show that it recovers the correct parameters if we target a synthetic set of moments generated by our own model. Specifically, we proceed as follows. First, we generate two random vectors of parameters in the neighborhood of the estimated baseline parameters. Second, we use the model to generate one set of moments from each of the three vectors of parameters (our main estimates, and the two random ones). Third, we run three separate estimation procedures targeting each set of these synthetically generated moments. We keep all the inputs identical across the three estimations, and we follow step by step our methodology described above.

The results from this exercise are shown in Figures A6 and A7. Figure A6 follows closely the previous Figure A4. The stars on the x-axis show the values of the baseline (black) and the randomly generated parameters (blue and red). The densities show the 10 best outcomes for each string from our estimation procedure targeting the moments that were synthetically generated from these parameters. The dashed vertical lines indicate the final parameter estimates given these moments. Overall, our estimates are close to the correct parameter values. Figure A7 further reinforces this point by plotting our estimates against the true parameters, together with a 45 degrees line. While the fit is not perfect, overall our estimates are always close to the true values, suggesting that all parameters are very well identified.

Figure A7: Estimated Parameters vs their True Values



Notes: Each panel shows a different parameter, as shown on its title. The x-axis shows the true parameter values, while the y-axis shows our estimates. Each panel has three dots representing the three different estimations (and sets of parameters/moments). The dashed black line is the 45 degrees line.

H Further Details on Model Fit

This section presents additional figures and tables to describe the model fit with the data. While all the moments are included here in figures, we explicitly present their (305) numerical values in tables in Supplemental Appendix U.

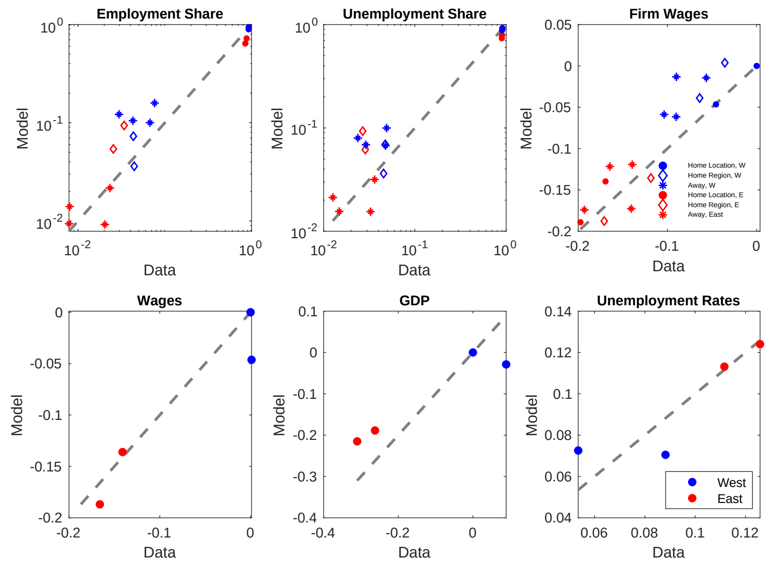
Figure A8 shows that the model fits well the empirical moments on distribution of employment, output and wages across locations and by workers types. Each panel plots a set of moments in the data (x-axis) against their values in the model (y-axis), with the 45-degree line indicating a perfect fit.

Figure A9 plots the firm size distributions in each location in the model and in the data. The model matches almost perfectly the share of employment in the middle of the size distribution, and only slightly underestimates the mass of employment at the bottom and top deciles. In each location, approximately half of the overall employment is accounted for by the largest decile of firms.

Table A8 shows that the model also does a reasonable job in matching the joint distributions of firm wages, sizes, and separation rates, the standard deviation of wage gains, and the profit shares. The core mechanism of the model generates a positive relationship between firm size and firm wage (row 1 of Table A8), since higher productivity firms offer higher wages to increase their size. As a result, workers climb a job ladder across firms and are more likely to separate at the bottom rungs (row 2), also facing, on average, larger wage gains when separating from firms at the bottom (row 3). These core features of the model are consistent with the data. We further explore these relationships in Figure A11, where we plot these variables in the model and in the data non parametrically, for each of the four locations. In both the model and data, these relationships are roughly linear.

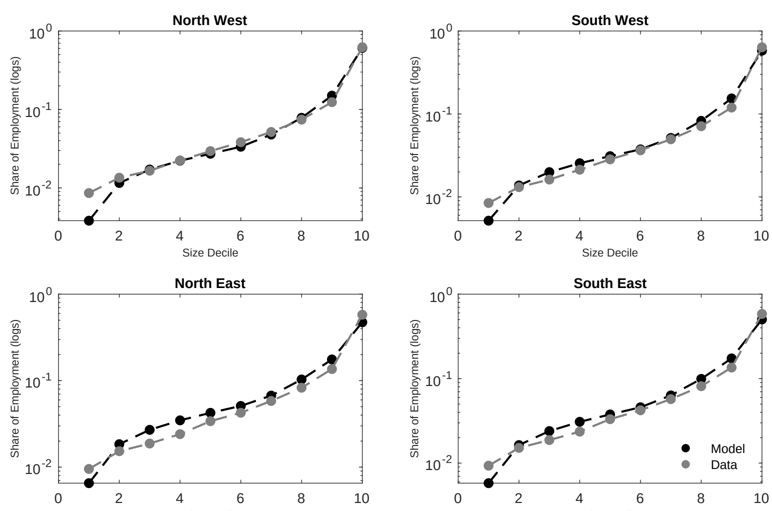
As noted in the main text, the model overestimates the relationship between job movers' expected wage gains and their current firm's average wage. Moreover, the model underestimates the standard deviation of wage gains of movers (row 4 of Table A8). This result is somewhat expected since in the model wage dispersion across firms is purely generated by labor market frictions, while in the data there may be other sources of wage dispersion that our empirical controls are not capturing. For further analysis, Figure A10 plots the distribution of the standard deviation of wage gains in the model and data for all 64 origin-destination-home location tuples. The standard deviations in the data are higher than in the model for nearly all combinations of moves. For comparison, we also plot in the figure an alternative empirical moment: the standard deviation of wage gains controlling for individual fixed effects (light gray). As expected, controlling for individual fixed effects reduces significantly the empirical variance (some individuals have persistently higher wage gains than others, as shown in the literature). Relative to this alternative target, our model slightly overestimates the standard deviation of wage gains.

Figure A8: Employment, Wages, and GDP by Location and Worker-Type



Notes: The figure graphs the value of various moments in the model against the same moments in the data. The construction of these moments is described in Supplemental Appendices Q.2.3 to Q.2.8. Each dot corresponds to one moment. The top left panel shows the share of employed workers residing in each location, by worker type. The top middle panel shows the share of unemployed workers residing in each location, again by worker type. The top right panel shows the average log firm component of wages for each worker type residing in each location, normalized relative to workers whose home location is North-West and that are currently residing in the North-West. In each panel, moments relating to West German workers are in blue and moments for East German workers are in red. Circles are for workers currently residing in their home location, squares for workers residing in their home region but not location, and stars are for workers currently out of their home region. The bottom left panel shows the average log firm component of wages by location, relative to the North-West. The bottom middle panel shows the GDP per capita of each location relative to the North West. Last, the bottom right panel shows the unemployment rates. In each of these panels, West locations are in blue and East locations are in red.

Figure A9: Within-Location Firm-Size Distributions



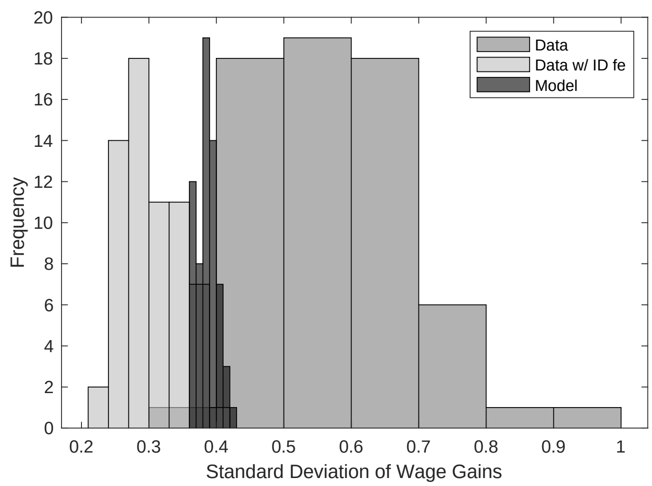
Notes: The figure compares the firm size distribution in the model and in the data. Each panel graphs the share of total employment that is working at each decile of the firm size distribution for each of the four locations. Model moments are in black and data moments are in gray. The construction of these moments is described in Supplemental Appendix Q.2.9.

Table A8: Model Fit for Additional Moments

	Parameters		Model West	Model East	Data West	Data East
(1)	Slopes wage vs firm's size, by j	*North*	0.126	0.135	0.124	0.110
		South	0.161	0.140	0.124	0.109
(2)	Slopes separation vs firm's wage, by j	*North*	-0.024	-0.019	-0.029	-0.037
		South	-0.024	-0.020	-0.033	-0.036
(3)	Slopes wage gain vs firm's wage, by j	*North*	-0.805	-0.889	-0.549	-0.561
		South	-0.827	-0.870	-0.577	-0.562
(4)	Average Std of job-job wage gains, by j	*North*	0.392	0.377	0.591	0.584
		South	0.399	0.378	0.609	0.539
(5)	Profit shares, by j	*North*	0.285	0.360	0.274	0.259
		South	0.303	0.342	0.259	0.263

Notes: The table compares several moments in the model to their data analogues, by location of the firm. The construction of these moments is described in Supplemental Appendices Q.2.10 to Q.2.14. The first row shows the slope of the wage function with respect to firm size. The second row presents the slope of the separation rate with respect to firms' wage. The third row shows the slope of the average wage gain from a job-to-job move as a function of the origin firm's wage. The fourth row presents the standard deviation of wage gains from a job-to-job move by location of the origin firm. We take the average across all the 16 possible job-to-job moves that originated in each region. All the 64 disaggregated moments are included in Supplemental Appendix U. The last row shows the average ratio of profits to labor costs in each location.

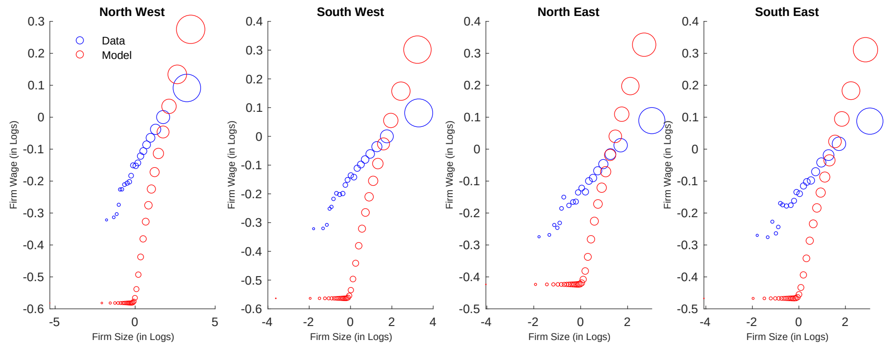
Figure A10: Standard Deviation of Wage Gains



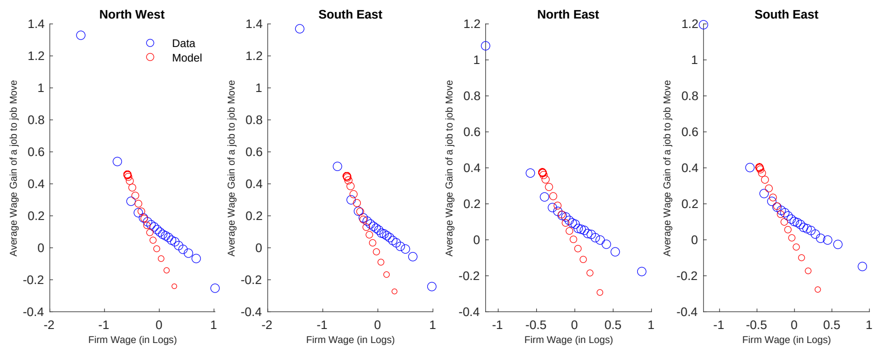
Notes: The figure shows the distribution of the standard deviation of wage gains for all the 64 possible tuples of origin-destination-home location (j, x, i). The empirical moments are computed in Supplemental Appendix Q.2.13. The histogram counts the frequency with which a standard deviation of wage gains of the given value is observed. The count in the model is depicted by the black bars and the count in the data in dark gray. The light gray bars present an alternative empirical specification where, in addition to the controls in Supplemental Appendix Q.2.13, we include individual fixed effects in the regression that residualizes the wage gains. The width of the bars is chosen so that each alternative has the same number of bars. It varies across alternatives dependent on how dispersed the standard deviations are. The height of the bars is comparable across alternatives and indicates the number of observations falling into the given range of standard deviations.

Figure A11: Fit for Joint Distribution of Firm Wages, Sizes, and Separation Rates

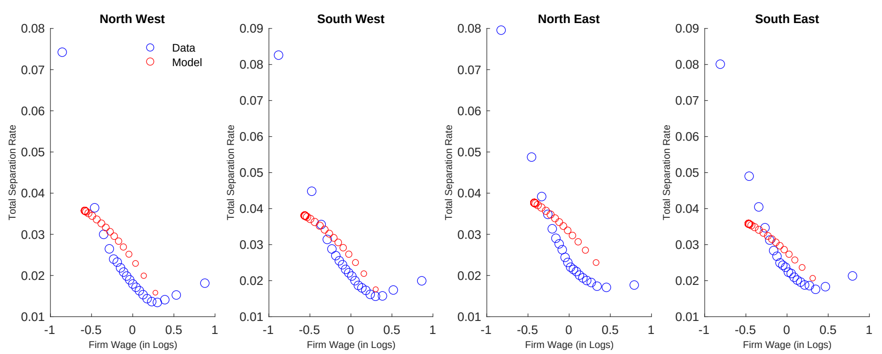
(a) Relationships between Firm Sizes and Average Wages



(b) Relationships between Firm Wages and Expected Wage Gains of Job-to-Job Moves



(c) Relationships between Firm Wages and Separation Rates



Notes: The figure compares various moments in the model (red) and in the data (blue), for each location. The empirical moments are computed as described in Supplemental Appendices Q.2.10 to Q.2.12. In both the data and the model, we cut the firm distribution into twentiles based on the variable on the x-axis and then compute the summary statistic within each twentile. The size of each circle represents the number of observations. Wages and sizes are normalized relative to their average in both model and data without loss of generality since they are not targeted. The top panels show the relationship between firms' average wage and their size (number of workers). The middle panels show the relationship between the average wage gain of a job-to-job move, across all possible moves, and the average wage of the worker's firm prior to the move. The bottom panels show the relationship between the rate at which workers separate, either towards a new firm, unemployment, or permanent non-employment, and the average wage of the firm prior to the move.

I Evidence Supporting the Model Mechanism

We provide further evidence supporting the model's mechanism from the NY Fed's Survey of Consumer Expenditures (SCE) job search supplement for the years 2013-2020. The data is a series of repeated cross-sections with roughly 1,200 individuals each year. We use a confidential version of the data which identifies respondents' ZIP codes and individual demographic information. We merge each worker to the total employment in the worker's industry and commuting zone (CZ) using the Census Bureau's County Business Patterns (CBP), and obtain the wage distribution of the worker's industry and CZ from the 5-year American Community Survey (ACS) for 2015-2019. We provide more information on data preparation in Supplemental Appendix X.

We first analyze the effect of commuting time on employed workers' search behavior by running:

$$y_i = \beta_1 \ln(wage_i) + \beta_2 \ln(comm_i) + \alpha X_i + \epsilon_{ins}, \tag{36}$$

where y_i is the inverse hyperbolic sine (IHS) transformation of either i) employed worker i's number of applications sent to employers in the last four weeks; or ii) the number of hours spent searching for jobs in the last seven days. We use the IHS since many workers report zeros. The variable $wage_i$ is the worker's weekly wage at the current job, $comm_i$ is the commuting time in minutes, and X_i contains controls for gender, age dummies, a dummy for a college degree, industry fixed effects, and state fixed effects. The first two columns of Table A9 show that a greater commuting time for a given wage is positively associated with search effort.[67]

Second, we add to regression (36) dummies for whether the worker's current wage is in the second, third, or fourth quartile of the industry-CZ wage distribution. We focus on applications as our outcome variable; the results with search effort are similar and in Supplemental Appendix X. Columns 3 and 4 show that conditional on commuting time and wage, workers at the bottom of the wage distribution send more applications, consistent with our model.

Third, we add to the regression the total number of workers employed in the worker's industry and CZ. This variable is a measure of the density of the job market in the worker's location. In column 5, we use as LHS variable the worker's reservation wage for accepting a new job, and find that it rises with the density of the local job market, conditional on the current wage. In columns 6 and 7 we find that workers' search effort conditional on current wage is higher when the local job market is denser, even controlling for commuting time. Overall,

[67] In Supplemental Appendix X, we show that greater job dissatisfaction is also positively related to search effort.

these results highlight that the local labor market matters for workers' search decisions as highlighted by our model.

Table A9: Effect of Local Labor Market on Search

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$Apps_i$	$Search_i$	$Apps_i$	$Apps_i$	$\ln(ResWage_i)$	$Apps_i$	$Apps_i$
$\ln(wage_i)$	$-$**.1294***	$-$**.1077***		$-.0376$	**.5145***	$-$**.1300***	$-$**.1329***
	(.0192)	(.0127)		(.0277)	(.0352)	(.0214)	(.0217)
$\ln(comm_i)$	**.0333****	**.0359****	**.0289***	**.0301****	.0152		**.0249***
	(.0131)	(.0131)	(.0149)	(.0149)	(.0150)		(.0150)
$wage_i(Q2)$			$-$**.1928*****	$-$**.1605*****			
			(.0414)	(.0471)			
$wage_i(Q3)$			$-$**.2657*****	$-$**.2187*****			
			(.0400)	(.0523)			
$wage_i(Q4)$			$-$**.3623*****	$-$**.2914*****			
			(.0397)	(.0646)			
$\ln(emp_i)$					**.0253****	**.0198****	**.0179****
					(.0109)	(.0081)	(.0082)
Industry FE	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y
Age, Sex, Ed	Y	Y	Y	Y	Y	Y	Y
Obs	4,960	4,960	4,150	4,150	3,344	4,151	4,151

Source: SCE and authors' calculations. Notes: Regressions are run on individual-level data for 2013-2020. $Apps_i$ is the IHS of the number of job applications sent by worker i in the last four weeks. $Search_i$ is the IHS of the number of hours spent searching for jobs in the last seven days. $ResWage_i$ is the reservation wage demanded for accepting a new job for workers looking for other employment. $wage_i$ are the weekly earnings at the main job. $comm_i$ is the average time spent commuting to the main job each day. $wage_i(Qx)$ is a dummy for whether the worker's weekly earnings are in the x percentile of worker i's commuting zone by industry wage distribution from the ACS. emp_i is the total employment in worker i's industry in her commuting zone from the CBP. Industries are 2-digit NAICS industries. Age controls are dummies for < 25, $25-54$, and 55+ years. Sex is a dummy for males. Ed is a dummy for a bachelor's degree.

J Additional Quantitative Results

Robustness. We explore the quantitative role of two key assumptions of our model: (i.) there are only two locations in each region; (ii.) the locations in East Germany are smaller, hence have fewer firms and workers.

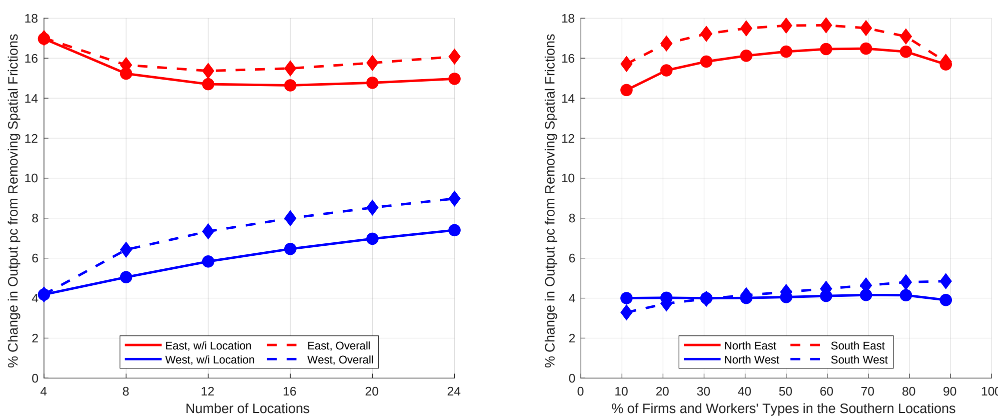
First, we vary the number of locations. We solve a version of our model in which we split each of the four locations in the benchmark model into either 2, 3, 4, 5, or 6 sub-locations. We randomly draw each sub-location k's average firm productivity, $A_j(k)$, from a normal distribution with mean equal to the overall location's estimated productivity, A_j, and standard deviation equal to the East-West productivity gap to allow for possibly large gains from the reallocation of labor across the sub-locations. We keep the spatial frictions exactly as estimated in the baseline, and we split the workers' types to match the new locations.[68]

Figure A12a shows that we continue to find large gains from the within-location reallocation of labor even as we increase the number of locations. Intuitively, there is significant scope for within-location reallocation due to substantial heterogeneity across firms, and congestion forces due to prices and labor market tightness limit the gains from labor reallocation across space.

Second, we vary the labor market size. We proportionally vary the mass of firms (M_j) and workers $\left(\bar{D}_j^i\right)$ that are in the South versus in the North in both East and West Germany, keeping the total mass of workers and firms in the overall region and the other structural parameters constant. Figure A12b shows that increasing the mass of workers and firms in the South relative to the North has only small effects on the aggregate gains in both locations. While removing spatial frictions gives firms in smaller locations a bigger relative increase in the mass of workers that can now apply to their vacancies, they also face a relative bigger increase in competition. These two effects roughly balance each other out.

Figure A12: Aggregate Cost of Spatial Frictions as a Function of Size and Number of Locations

(a) Number of Locations (b) Location Size



Notes: The left panel shows the change in output per capita from removing spatial frictions computed for East Germany (in red) and West Germany (in blue) as we vary the overall number of locations. The solid lines show the average of the gains from within-location reallocation across all locations in the region. The dashed lines show the total gains, including from reallocation across locations. The right panel shows the change in the output per capita for the two locations in the East (in red) and the two in the West (in blue) plotted as a function of the share of the population in the Southern locations.

[68] Two complications arise. First, we need to recompute the distance between the new sub-locations. Given the scope of this exercise, we keep the average distance between locations as in the baseline, and we assign the sub-locations to be equally distanced on a line. Second, we need to re-normalize the search productivity z as we vary the number of sub-locations, since otherwise the overall ability of workers to search would scale up. We proportionally scale all z_{jx}^i so that $\sum_{x\in\mathbb{J}} z_{jx}^i$ is constant across all scenarios.

Regional Gaps. Table A10 provides another perspective on the results by showing the percentage differences in our variables of interest between East and West Germany and between East and West German workers. Eliminating spatial frictions shrinks the gaps in output, value, and wages considerably, but does not eliminate them. The remaining East-West gap is due to the average higher productivity of firms in the West, the higher estimated amenity in the East, and the presence of labor market frictions. The gap between East and West Germans is purely due to the estimated differences in workers' skills θ.

Table A10: West-East Gaps with Reduced Spatial Frictions

			Baseline	All Frictions	w/i Locations	Partial Eq.	Technology	Preferences
			(1)	(2)	(3)	(4)	(5)	(6)
By Region	(1)	Output pc	30.3 %	16 %	26 %	18.9 %	19.2 %	24.8 %
	(2)	Value Function	15.8 %	0.4 %	6.9 %	0.8 %	1.7 %	9.1 %
	(3)	Wage	35.4 %	17.9 %	28.3 %	25.6 %	24.4 %	26.9 %
	(4)	Real Wage	26 %	13.6 %	23.5 %	20.3 %	18.9 %	18.6 %
	(5)	Wage (per eff. unit)	25.6 %	17.9 %	19 %	25.6 %	23.7 %	21.3 %
By Birth	(6)	Output pc	26.4 %	11.2 %	23.4 %	11.2 %	13.1 %	19.7 %
	(7)	Value Function	18.7 %	8.3 %	8.5 %	9 %	10.7 %	13.4 %
	(8)	Wage	29.8 %	11.7 %	25.1 %	11.7 %	14.3 %	20.6 %
	(9)	Real Wage	23.5 %	11.7 %	21.8 %	11.7 %	14 %	17.2 %
	(10)	Wage per eff. unit	18.1 %	1.7 %	13.8 %	1.8 %	4 %	9.7 %
	(11)	% of West-born in the West	96.7 %	69.3 %	96.7 %	71.6 %	73.5 %	89.9 %
	(12)	% of East-born in the West	25.5 %	69.1 %	25.5 %	71.1 %	66.9 %	46.1 %

Supplemental Material – Not for Publication

K Further Details on Data and Data Construction

In this section, we provide further details on the variables used in the paper and provide some summary statistics.

BHP Data We construct three age variables. We compute each firm's number of young full-time employees (15-29 years old, az_15_19_vz + az_20_24_vz + az_25_29_vz), the number of medium-aged employees (30-49 years old, az_30_34_vz + az_35_39_vz + az_40_44_vz + az_45_49_vz), and the number of older employees (50-64 years old, az_50_54_vz + az_55_59_vz + az_60_64_vz). We construct three education variables. We obtain the number of full-time workers with low qualifications (az_gq_vz), covering individuals with a lower secondary, intermediate secondary or upper secondary school leaving certificate but no vocational qualifications. We obtain the number of full-time workers with medium qualifications (az_mq_vz), which includes workers with a lower secondary, intermediate secondary, or upper secondary school leaving certificate and a vocational qualification. Finally, we use the number of full-time workers with high qualifications (az_hq_vz), which encompasses workers who have a degree from a university of applied sciences (Fachhochschule) or a university.

Our final dataset contains 4,797,798 firm-year observations. Table S1 provides some summary statistics.

Matched LIAB-BHP Data The matched data include only those firms in which at least one worker in the LIAB has an employment spell. Table S2 presents some statistics. We find that this sample contains about 40% of the firm-year observations of our BHP sample above. Firms that are matched to the LIAB pay on average about 10% higher wages and are on average about three times larger than firms in the stand-alone BHP. The skew towards larger firms is expected since larger firms are more likely to be matched to at least one worker. Due to this lack of representativeness of the matched LIAB-BHP matched sample, we rely on the BHP sample to compute the firm-level moments we use in our model estimation.

LIAB data We provide more details on how we define unemployed and employed workers. We record an individual as unemployed if her employment status (erwstat) is 1 (ALG Arbeitslosengeld, which means "Unemployment benefit"), 2 (ALHI Arbeitslosenhilfe, "Unemployment benefits"), 3 (UHG Unterhaltsgeld, "Maintenance allowance"), or 5 (PFL Beitraege zur Pflegeversicherung, “Contributions to long-term care insurance”). The remaining workers are employed. We define full-time employed workers as those that do not have a part-time flag (teilzeit), that are not in semi-retirement (Altersteilzeit), interns, working students, marginally employed, or apprentices based on their employment status (erwstat).

Table S3 provides some summary statistics of the LIAB data.

Locations for the Quantitative Estimation. Table S4 provides some summary statistics of the four locations in our estimation. The Northwest location is slightly bigger than the Southwest based on the number of workers, while the Northeast and the Southeast are very similar. Unemployment in both regions is higher in the North than in the South. Real wages are very similar across the locations within East and West Germany, with a significant wage gap between the two.

Table S1: Summary Statistics of the BHP Dataset

	Variable	Obs	Mean	Std. Dev.
(1)	Real wage of FT workers	4,797,798	74.319	40.370
(2)	Number of FT workers	4,797,798	11.516	78.068
(3)	Share male	4,797,798	0.562	0.417
(4)	Share young	4,781,174	0.222	0.310
(5)	Share medium-aged	4,781,174	0.515	0.360
(6)	Share older	4,781,174	0.263	0.329
(7)	Share low-skilled	4,741,107	0.070	0.196
(8)	Share medium-skilled	4,741,107	0.804	0.310
(9)	Share high-skilled	4,741,107	0.125	0.264

Notes: The table presents summary statistics across all firm-year observations in our data for some key variables in 2009-2014. “Real wage of FT workers” is the real daily wage of full-time workers. Young workers are defined as those between 15-29 years old. Medium-aged workers are those between 30-49 years old. Older workers are those between 50-64 years old. Low-skilled workers are those with a lower secondary, intermediate secondary or upper secondary school leaving certificate but no vocational qualifications. Medium-skilled workers are those with a lower secondary, intermediate secondary, or upper secondary school leaving certificate and a vocational qualification. High-skilled workers are those with a degree from a university of applied sciences (Fachhochschule) or a university.

Table S2: Summary Statistics of the Matched BHP Dataset in the LIAB

	Variable	Obs	Mean	Std. Dev.
(1)	Real wage of FT workers	2,003,150	81.510	40.921
(2)	Number of FT workers	2,003,150	38.971	207.164

Notes: The table presents statistics across firm-years in the BHP data that is matched to the LIAB for 2009-2014. We only keep firm-year observations with at least one full-time worker. “Real wage of FT workers” presents the mean and standard deviation of the average real wage of full-time workers across firm-years.

Table S3: Summary Statistics of the LIAB Dataset

	Variable	Obs	Mean	Std. Dev.
(1)	Real wage of FT employed	7,963,537	111.890	76.967
(2)	Real wage of unemployed	1,254,063	27.580	12.469
(3)	Employed dummy	9,485,701	0.849	0.358
(4)	Age	9,485,701	40.172	11.538
(5)	Male dummy	9,485,701	0.696	0.460
(6)	College dummy	5,904,697	0.205	0.403
(7)	Work county East	9,485,701	0.294	0.455
(8)	Live county East	9,485,701	0.310	0.463
(9)	Home county East	9,376,568	0.321	0.467

Notes: The table presents unweighted averages across all employment and unemployment spells in our core sample period for some key variables. Row 1 shows the real daily wage of full-time employed workers. Row 2 shows the real daily wage (or income) of unemployed workers. Row 3 presents the value of a dummy that is one for employment spells. Row 4 shows the average age, and row 5 shows the average of a dummy that is one for male workers. Row 6 shows the average of a dummy that is one for college educated workers. This variable is only available for employed individuals. Rows 7-9 present the averages for dummies that are one if the individual works, lives, and has home county in the East, respectively.

Table S4: Descriptive Statistics of the Locations

		NW	SW	NE	SE
(1)	Individuals by work location	355,907	304,158	125,377	131,959
(2)	Unemployment rate	8.8%	5.4%	12.6%	11.2%
(3)	Real GDP per capita	35,119	38,391	25,756	27,016
(4)	Average real wage	76.44	76.49	64.18	64.54

Source: BHP, LIAB, German Federal Employment Agency, National Accounts of the States, and own calculations. Notes: The table presents summary statistics for the four locations used in the estimated model. The first row shows the average number of individuals per year in our sample period 2009-2014 in each location, according to their work location. For unemployed workers, we use the last work location. Row 2 shows the average unemployment rate (Arbeitslosenquote bezogen auf abhängige, zivile Erwerbspersonen), computed as a population-weighted average across the states of each location, from the German Federal Employment Agency. Row 3 presents the real GDP per capita, computed as a population-weighted average across the states of each location, from the National Accounts of the States (Volkswirtschaftliche Gesamtrechnungen der Länder, VGRdL). The last row shows the average real wage paid by the firms in each location from the BHP.

L Additional Results on the Wage Gap

We provide several robustness checks to show that the large East-West wage gap is not driven by observables, outliers, or compositional issues. We next show that there is a large unemployment gap between East and West Germany. We then provide additional details on the joint distribution of wages and firm size within each region and show that large wage heterogeneity exists even within individual counties. Finally, we show that there are no systematic differences in tax rates between East and West Germany.

Additional Controls and Worker Composition. We run specification (1) to investigate the role of different controls in explaining the wage gap, and present the results in Table S5. All regressions are weighted by firm size. Including controls for the firm's share of males and the share of workers with medium qualifications and high qualifications (column 2) and average worker age and firm size (column 3) do not contribute significantly to the wage gap. Controlling for 3-digit industries narrows the gap slightly (column 4), but overall about 80% of the real wage gap remains unexplained.

Table S6 displays the results from running regression (1) without weighting by firm size. As expected, the wage gap is slightly smaller when we do not give more weight to larger firms, which tend to pay higher wages. However, the results remain somewhat similar to before. Adding the controls does not reduce the wage gap.

Figure S1 depicts the CDF of average real wages across German counties. Each dot is a county, ranked by average real wage, where the steepness of the CDF is determined by the share of each region's population captured by the county. Eighty percent of people in West Germany live in a county with an average real wage higher than the highest wage county in East Germany (marked by the red dashed line). Thus, the wage gap is not driven by a few high-wage counties in West German metropolitan areas; rather, Figure S1 shows that there is a systematic shift in the wage distribution.

We next examine education, industry and gender differences between regions. Figure S2a plots the CDF of the share of workers with a college degree by county. Average college attainment is more homogeneous in the East than the West, but both regions have similar maximum levels of education in their top counties. Figure S2b illustrates that wages are lower in the East at every education level.

Figure S3a portrays the average wage in each industry in the East (x-axis) plotted against the average wage in each industry in the West (y-axis). Almost all of the industries lie above the 45 degree line indicating nearly uniformly higher wages in the West. Figure S3b shows that industries straddle the 45 degree line when plotting the percent of college educated workers in the East (x-axis) and the West (y-axis), and thus there is no systematic education difference within industries.

Figure S4 plots each county's average real wage (y-axis) against the share of male workers (x-axis). There is a slight positive correlation between the counties with a higher percentage of male workers and higher average wages. Most of the Western counties have higher male proportions and also higher wages. However, as shown in the main text, controlling for education, age, gender, and industries in regression (1) explains only a small part of the overall wage gap.

Unemployment. Figure S5 shows that there is a large East-West gap in average unemployment between 2009 and 2014. The level of unemployment in East Germany is about 5 percentage points higher than in the West, although there is some heterogeneity across counties. Consistent with this empirical fact, our model will generate higher unemployment in the East compared to the West.

Within-Region Wage Distributions. We next turn to the within-region wage distributions. Figure S6 provides some additional information about the wage and firm size distributions within East and West Germany. As in the main text, we remove variation due to observables that is not present in our model by performing, for both East and West Germany, the following regression

$$\ln(y_{jrt}) = B_r X_{jrt} + \gamma_t + \epsilon_{jrt}, \tag{37}$$

where y_{jrt} is either the number of full-time workers of firm j in region r (either East or West Germany) in year t or their average wage, and γ_t are year fixed effects. The controls X_{jrt} are 3-digit time-consistent industry dummies based on Eberle et al., 2011 (WZ93 classification). We obtain from these two regressions residuals for the log real wage, $\hat{\epsilon}_{jrt}^{wage}$, and for the log number of workers, $\hat{\epsilon}_{jrt}^{size}$. We add back the mean of each variable in each region, $\overline{\ln(y_{jrt}^{wage})}$ and $\overline{\ln(y_{jrt}^{size})}$, to obtain a cleaned real wage, $\hat{y}_{jrt}^{wage} = \exp[\overline{\ln(y_{jrt}^{wage})} + \hat{\epsilon}_{jrt}^{wage}]$ and a cleaned number of workers, $\hat{y}_{jrt}^{size} = \exp[\overline{\ln(y_{jrt}^{size})} + \hat{\epsilon}_{jrt}^{size}]$ for each firm. We then generate twentiles of the cleaned wages and firm sizes, and compute the joint distribution of cleaned wage and size across all firms and years in our core sample period.

The top left panel of Figure S6 shows the density of the cleaned real wage in East and West Germany. The figure shows that the wage distribution in the West is basically the East German wage distribution shifted to the right. The top right panel shows the density of the cleaned firm size variable, and it shows that the size distributions essentially lie on top of each other. There is a slightly longer right tail of very large firms in West Germany, which could be the result of more large firms having their headquarters in the West. The bottom left panel presents cuts of the joint distribution of wage and size by plotting the density of the wage distribution at different percentiles of wages, for "small" firms (all firms up to the 15th percentile of the size distribution), "medium" firms (all firms between the 45th and 55th percentile), and "large" firms (above the 85th percentile), in both East and West Germany. The bottom right panel plots the cleaned wage against the cleaned size as already shown in the main text. We see that the relationship in West Germany is a parallel shift of the relationship in the East, with West German firms paying a higher wage at each firm size.

Within-County Wage Dispersion. We next re-run equation (37), but include in the controls X_{jrt} not only industry dummies but also county fixed effects, the share of male full-time workers, the share of young full-time workers (of age less than 30 years old), and the share of full-time workers of medium age (30-49 years old). The controls also include the share of full-time workers of low qualification (individuals with a lower secondary, intermediate secondary, or upper secondary school leaving certificate but no vocational qualifications) and the share of full-time workers of medium qualification (individuals with a lower secondary, intermediate secondary, or upper secondary school leaving certificate and a vocational qualification). The resulting cleaned wages thus capture within-county, within-industry variation that is cleaned of some observable characteristics of the workforce. We generate deciles for the cleaned wages similarly to before and plot the resulting densities in East and West Germany in Figure S7. Despite the rich set of controls, we still find substantial wage heterogeneity across firms, even within county and industry.

Tax Rates. We next discuss whether there are significant differences in tax rates between East and West Germany. For example, if income tax rates in the East were lower, then the after-tax income gap between East and West could be smaller than our results suggest. However, we do not find systematic tax differences, as we show next.

First, the income tax and the value-added tax are the same anywhere in Germany.[69] Similarly, the corporate tax rate is the same.[70]

Second, all companies are subject to a business tax that is levied at the level of the individual

[69] see http://www.buzer.de/gesetz/4499/index.htm and https://www.export.gov/article?id=Germany-VAT.

[70] https://europa.eu/youreurope/business/taxation/business-tax/company-tax-eu/germany/index_en.htm

community. The tax consists of the product of i) the business income, ii) a base rate, and iii) a leverage ratio. The business income is computed in the same way across Germany, and the base rate is 3.5% everywhere. The leverage ratio varies across communities. Figure S8a shows these leverage ratios and highlights that there are no systematic differences between East and West.

Third, the government collects taxes on behalf of the church. This church tax is higher in the South than in the North of Germany, but does not vary between East and West (Figure S8b).

Finally, property taxes are relatively low in Germany, accounting for about 0.44% of GDP in 2010, significantly lower than in most of the EU (Paetzold and Tiefenbacher (2018)). There are two types of property tax, Property Tax A (for agricultural properties) and Property Tax B (for everything else). The latter accounts for the vast majority of tax receipts from this income source. The property tax is calculated as the product of i) the property's "rateable value", ii) a base rate, and iii) a leverage ratio.[71] The rateable value is determined by a federal law on valuations. For West Germany, it is determined by a land census in 1964, while, due to the division of Germany, the rateable value for property in East Germany is mostly still based on the census from 1935. The base rate depends on the type of building, with different rates for example for residential property and agricultural property. It also differs across East and West Germany, with East Germany having on average higher base rates for similar types of properties. Finally, the leverage ratio is determined at the level of the individual community. We present the leverage ratios for the two types of property tax in Figures S9a and S9b, displayed in percent (e.g., 180 means a collection rate of 180%). While there are significant differences in ratios across communities, the ratios are not systematically different between East and West Germany.

[71] See Bird and Slack (2002).

Table S5: Effect of Region on Real Wage

Dep var.: $\log(\bar{w}_{jt})$	(1)	(2)	(3)	(4)
$\mathbb{I}_{j,East}$	$-.\mathbf{2609}^{***}$	$-.\mathbf{2695}^{***}$	$-.\mathbf{2467}^{***}$	$-.\mathbf{2052}^{***}$
	(.0074)	(.0058)	(.0031)	(.0027)
Year FE	Y	Y	Y	Y
Gender & Education	–	Y	Y	Y
Age & Firm Size	–	–	Y	Y
Industry FE	–	–	–	Y
Observations	4,797,798	4,741,107	4,725,435	4,725,210

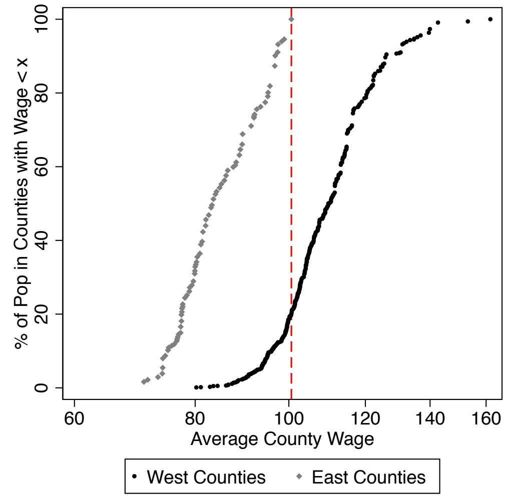
Source: BHP and authors' calculations. Notes: The table presents the estimates on the East Germany dummy from specification (1) for the period 2009-2014, where firms are weighted by size. $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the firm-level.

Table S6: Effect of Region on Real Wage (Unweighted Estimates)

Dep var.: $\log(\bar{w}_{jt})$	(1)	(2)	(3)	(4)
$\mathbb{I}_{j,East}$	$-.\mathbf{1600}^{***}$	$-.\mathbf{1876}^{***}$	$-.\mathbf{1942}^{***}$	$-.\mathbf{1743}^{***}$
	(.0013)	(.0012)	(.0011)	(.0010)
Year FE	Y	Y	Y	Y
Gender & Education	–	Y	Y	Y
Age & Firm Size	–	–	Y	Y
Industry FE	–	–	–	Y
Observations	4,797,798	4,741,107	4,725,435	4,725,210

Source: BHP and authors' calculations. Notes: The table presents the estimates on the East Germany dummy from specification (1) for the period 2009-2014. $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the firm-level.

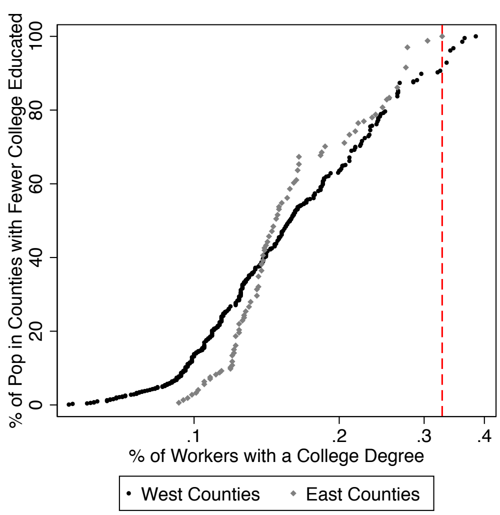
Figure S1: Cumulative Distribution Functions of Real Wages in East and West



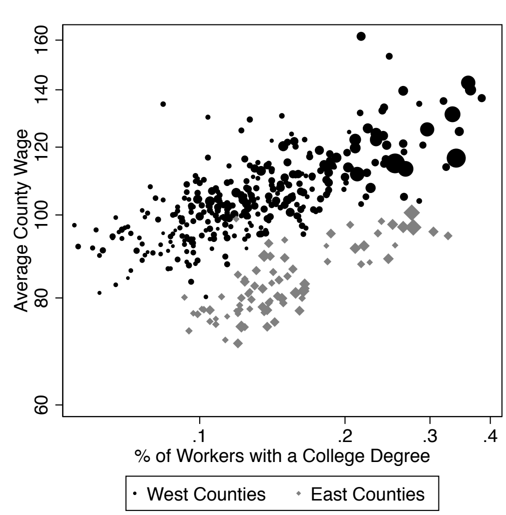
Source: BHP. Note: The figure shows the CDF of real wages across East and West German counties. Each dot is a county, where the steepness of the CDF is determined by the share of each region's full-time workers captured by the next county. Each county-level average wage is computed as a weighted average real wage across all firms in that county, using the number of full-time workers as weight. The red-dashed line shows the average real wage of the highest-paying county in East Germany.

Figure S2: Population and Real Wage by Education

(a) Share of Highly-Skilled Workers by County



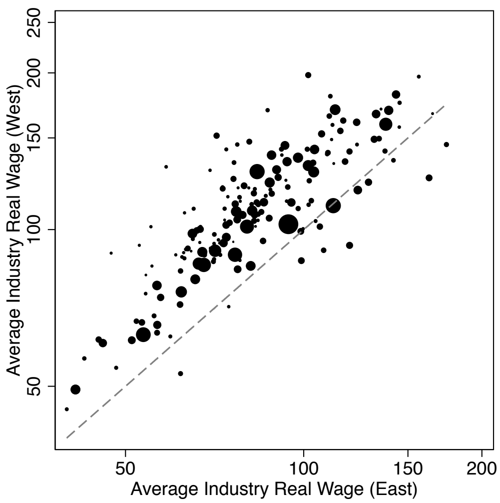
(b) Real Wage by Highly-Skilled Share Across Counties



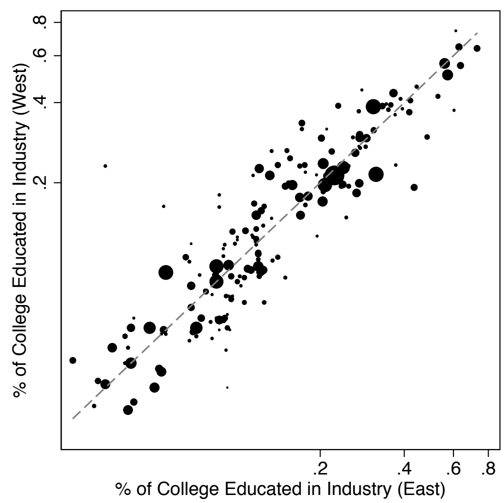
Source: BHP. Note: The left figure shows the CDF of the share of workers with a college degree in each county, where this share is calculated as the number of full-time workers with high qualification (az_hq_vz) divided by all full-time workers. Each dot is a county, where the steepness of the CDF is determined by the share of each region's full-time workers captured by the next county. The red-dashed line shows the maximum of the average share of high-skilled in East Germany. The right figure plots the share of college educated in each county against the average real wage of the county. The size of each dot is determined by the number of full-time workers in each county. Each county-level average wage is computed as a weighted average real wage across all firms in that county, using the number of full-time workers as weight.

Figure S3: Real Wage and Population by Industry

(a) Real Wage Gap by Industry

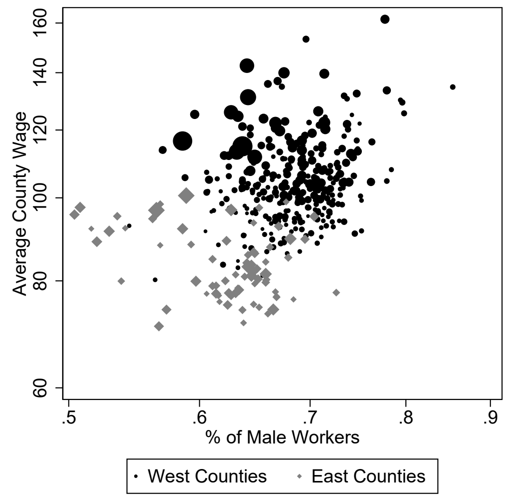


(b) Share of College-Educated by Industry in East vs. West



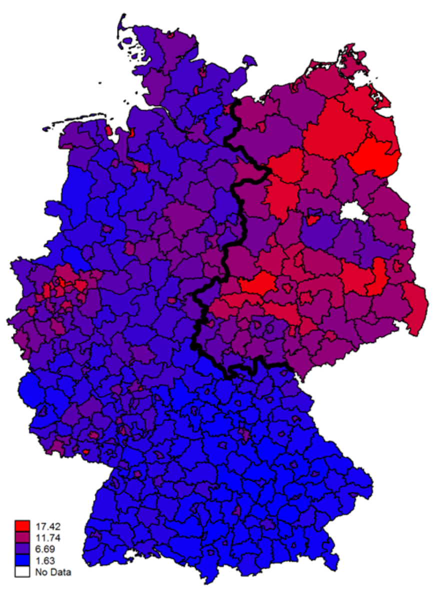
Source: BHP. Note: The left figure plots the average real wage in East Germany against the average real wage in West Germany at the industry-level. Each industry is a 3-digit WZ93 code, using the concordance by Eberle et al., 2011. Each industry-level average wage is computed as a weighted average real wage across all firms in that industry, using the number of full-time workers as weight. The right figure plots the share of college-educated workers in East Germany against the share of college-educated in West Germany at the industry-level, where the share of college-educated is calculated as the number of high-skilled full-time workers (az_hq_vz) divided by all full-time workers. The size of each dot is determined by the number of full-time workers in each industry.

Figure S4: Real Wage by Share of Males Across Counties



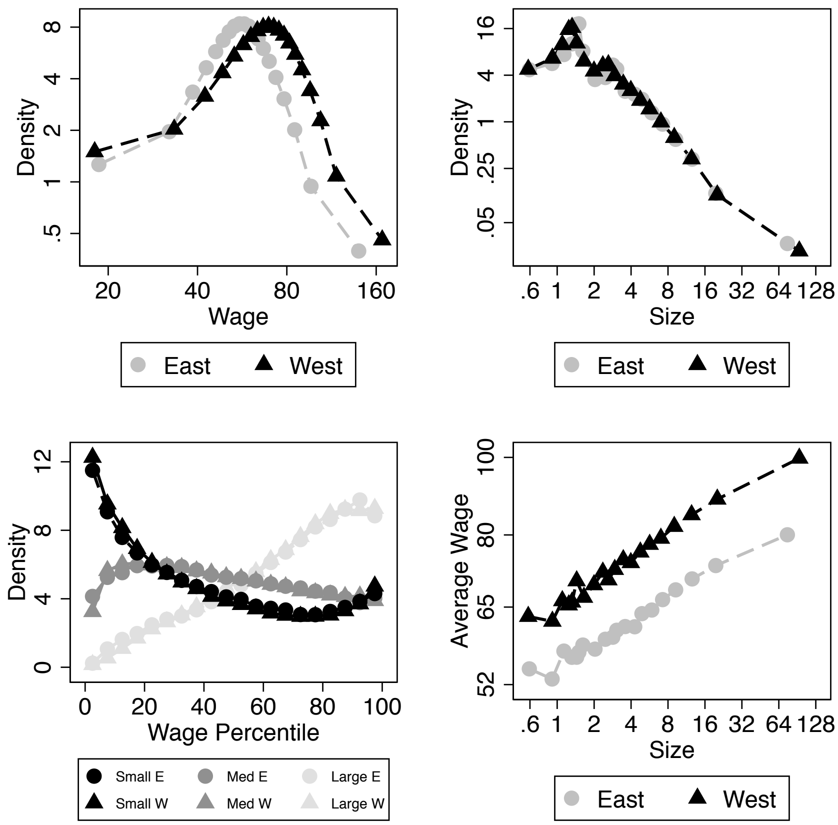
Source: BHP. Notes: The figure plots the share of full-time workers that are male in each county against the average real wage of the county. The average real wage in each county is computed as a weighted average over all firms in the county, using the number of full-time workers as weight. The size of each dot is determined by the number of full-time workers in each county.

Figure S5: Unemployment



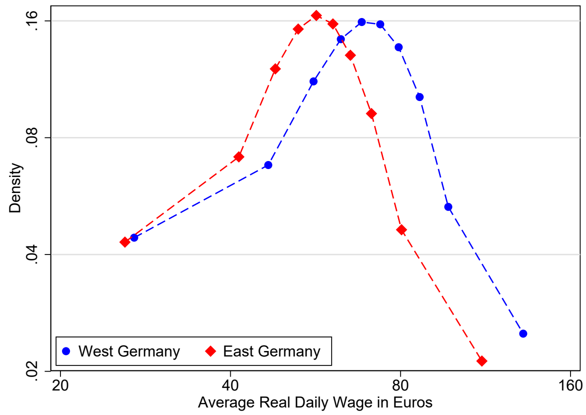
Source: Bundesagentur für Arbeit. Notes: The figure shows the average unemployment rate for each county in 2009-2014. Former East-West border is drawn in black for clarification. We exclude Berlin since we cannot assign it unambiguously to "East" or "West".

Figure S6: Firm Wage and Size Distributions in East and West



Source: BHP. Notes: The figure plots the joint distribution of firm size and wage in East and in West Germany. Both size and wage are residualized by regressing the log number of full-time workers and log real wage on 3-digit industry dummies and time dummies, for East and West Germany separately. We then generate the cleaned wage as the residuals from this regression plus the mean of the log wage in the given region. We perform a similar exercise for size. The top left panel shows the resulting wage distributions in East and in West Germany. The top right panel presents the size distributions. The bottom left panel presents cuts of the joint distribution by plotting the density of the wage distribution at different percentiles of wages, for "small" firms (all firms up to the 15th percentile of the size distribution), "medium" firms (all firms between the 45th and 55th percentile), and "large" firms (above the 85th percentile). The bottom right panel shows the firm size plotted against the wage.

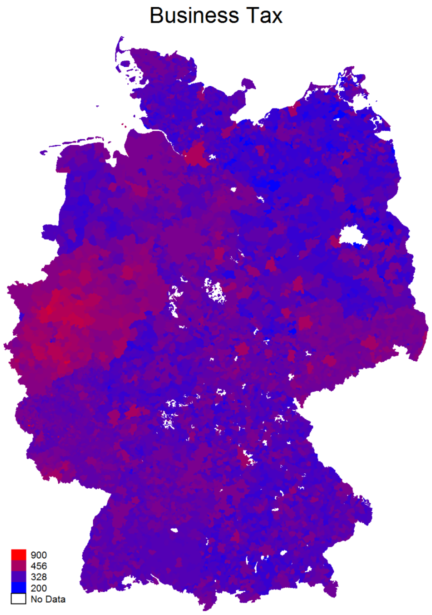
Figure S7: Firm Wage Distributions within County and Industry



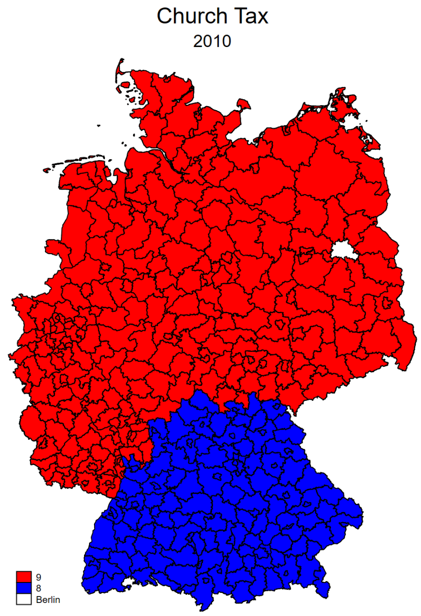
Source: BHP. Notes: The figure plots the densities of firm wages in East and in West Germany. The wage densities are residualized by regressing, for East and West Germany separately, the log real wage on 3-digit industry dummies, time dummies, county dummies, the share of male full-time workers, the share of young full-time workers (of age less than 30 years old), and the share of full-time workers of medium age (30-49 years old). The controls also include the share of full-time workers of low qualification (individuals with a lower secondary, intermediate secondary, or upper secondary school leaving certificate but no vocational qualifications) and the share of full-time workers of medium qualification (individuals with a lower secondary, intermediate secondary, or upper secondary school leaving certificate and a vocational qualification). We then generate the cleaned wage as the residuals from this regression plus the mean of the log wage in the given region. We obtain the deciles of the cleaned wage distribution, obtain the average wage in each decile, and transform the distribution into a density.

Figure S8: Business Tax and Church Tax

(a) Business Tax



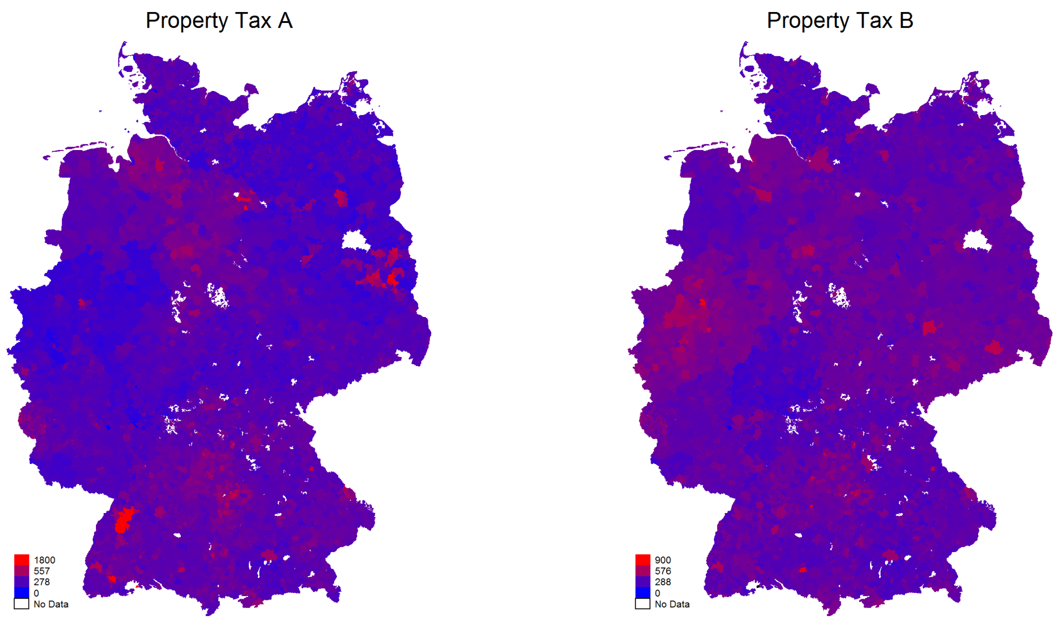
(b) Church Tax



Source: Statistical offices of the Federal States. Notes: The left panel plots the leverage ratio (Hebesatz) of the business tax rate (Gewerbesteuer) in each community in Germany in 2012, where a deeper shade of red indicates a higher leverage ratio. We omit Berlin since it is excluded from all of our analyses. The right panel shows the church tax (Kirchensteuer) in each county in Germany in 2010.

Figure S9: Leverage Ratios for Property Taxes

(a) Property Tax A (b) Property Tax B



Source: Statistical offices of the Federal States. Notes: The left panel plots the leverage ratio (Hebesatz) of the property tax A (for agricultural properties) in each community in Germany in 2012, where a deeper shade of red indicates a higher leverage ratio. We omit Berlin since it is excluded from all of our analyses. The right panel shows the leverage ratio for property tax B (for non-agricultural properties).

M Additional Results on Wage Gains for Job Movers

Baseline Regression. Table S7 shows the estimated coefficients for our baseline specification (2). These coefficients are used to generate Figures 2a-2b in the main text. Here, $d_{it}^{jk,l}$ is a dummy that is equal to one if worker i made a job switch of type l from region j to region k at time t, where j and k are either East (E) or West (W), and l is either migration as defined in the main text (m), commuting (c) or within-region (no indicator). As discussed, we find a large wage increase for migrants in the year after the move. For commuters, we find a smaller but still significant wage gain for moving across regions.

Regression with Individual Fixed Effects. Table S8 shows the results from a similar regression where we include individual fixed effects instead of male, college, and home region dummies. The wage gains are slightly smaller but very similar.

Keeping Year t. We next analyze an alternative specification where instead of dropping wages in year t we allocate these wages to years $t-1$ and $t+1$. Specifically, if an observation in year t is associated with a job move, we compute the weighted average wage in year $t-1$ as an average over the wages in year $t-1$ and the wages in year t prior to the job move, using the length of each job spell as weight. We similarly compute the weighted average wage in $t+1$ as an average over the wages in year $t+1$ and the wages in year t after the job move. If the observation in year t is not associated with a job move, we compute the weighted average wage in year $t-1$ as an average over the wages in $t-1$ and the wages until June of year t. Similarly, we compute the weighted average wage in $t+1$ as an average over the wages in year $t+1$ and the wages in year t after June. We then re-run regression (2) for $\tau \in \{t-3, ..., t-1, t+1, t+5\}$ with this definition. We sum up the estimated coefficients $\beta_{s,\tau}^{West}$ and $\beta_{s,\tau}^{East}$ starting in at $\tau = -3$ to obtain for each period τ the sum $\sum_{u=-3}^{\tau} \beta_{s,u}^{i}$, where $i \in \{\text{West}, \text{East}\}$, and subtract from this sum the term $\sum_{u=-3}^{-1} \beta_{s,u}^{i}$ to normalize the coefficients with respect to period $\tau = -1$. The resulting coefficients are plotted in Figures S10a-S10b analogously to the main text. The wage gains are very similar to the main specification.

Robustness. We next perform robustness checks to our baseline specification (2), where we focus on the wage change on impact by running

$$\Delta \log(w_{it}) = \sum_{s\in\mathbb{S}} \beta_s^{West} d_{it}^{s}(1 - \mathbb{I}_i^{East}) + \sum_{s\in\mathbb{S}} \beta_s^{East} d_{it}^{s} \mathbb{I}_i^{East} + BX_{it} + \epsilon_{it}, \tag{38}$$

where $\Delta \log(w_{it})$ is the log change between the weighted average wage in year $t+1$ after the move, where each wage is weighted by the length of its job spell, and the wage in the current job. As in the main text, d_{it}^{s} is a dummy for a job move of type $s \in \mathbb{S}$, containing the six possible types of moves: i) from East to West via migration or ii) commuting; iii) from West to East via migration or iv) commuting, v) within-East, and vi) within-West, and $\mathbb{I}_i^{East}$ equals 1 if individual i's home region is East Germany. As in the main text, the controls X_{it} include current work region by home region dummies, distance dummies since moves further away could lead to higher wage gains, the total number of past job-to-job switches, age controls, and year fixed effects. We present here the coefficients on the migration and commuting moves, which show the wage gains relative to stayers.

Column 1 of Table S9 shows the estimates from specification (38), where the superscripts indicate the direction of the move (East-West or West-East) and whether the move was migration (m) or commuting (c). Across the board, a migratory move incurs a larger wage gain than a commuting move. Migration moves of East Germans to the West are associated with very large wage gains, while return moves to the East only lead to a small wage increase, consistent with a home preference. In Column 2 we additionally control for the number of months passed between the previous job and the new job, and in Column 3 we consider only job-to-job moves where the time gap between jobs is less than two months to exclude workers that are out of the labor force between jobs. The results are preserved under these more stringent specifications, though the wage gains are smaller. In Columns 4-6 we return to our baseline setup but reclassify some moves that were previously classified as commuting as migration. Specifically, in Column 4 we add to migration those moves where the worker changes jobs between East and West Germany and the worker's distance to her residence increases, as long as the distance between work and residence is less than 200km for both jobs. We impose this threshold since a distance greater than 200km between residence and work likely indicates that the residence is misreported. In Column 5, we further broaden this definition and increase the threshold between work and residence from 200km to 350km. Finally, in Column 6, we define all job moves between East and West as migration (hence, there is no commuting). While wage gains from migration become smaller as we broaden the definition of migration, the overall pattern survives. In all specifications, East Germans moving to the West realize the largest wage gain out of any East-West-home combination. Additionally, with migratory moves, people moving back home to the East experience the lowest wage gains, if they experience any at all.

Demographic Groups. In Table S10 we apply our baseline regression (38) to certain demographic groups. For every East-West-home move combination, men (Column 1) realize smaller wage gains from migration than women (Column 2). Workers with a college degree (Column 3) realize a larger wage gain than those without one (Column 4). In terms of age, older workers born before 1965 (Column 7) see the lowest wage gains when moving and younger workers born after 1975 (Column 5) witness the largest wage gains. The overall pattern of the results is similar across all groups. Moving away from home generates larger wage gains than returning home.

Table S7: Wage Gains of Job-to-Job Moves (No Individual FE)

Dep var.:	Period τ						
$\log(\Delta w_{i\tau})$	t-3	t-2	t-1	t+1	t+2	t+3	t+4
$d_{it}^{EW,m}(\mathbb{I}_i^E = 0)$	.0052	−.0040	**−.0305*****	**.1698*****	**−.0160****	.0066	−.0036
	(.0107)	(.0099)	(.0097)	(.0126)	(.0071)	(.0073)	(.0081)
$d_{it}^{WE,m}(\mathbb{I}_i^E = 0)$	.0023	−.0072	**−.0273*****	**.1734*****	.0051	−.0015	.0079
	(.0088)	(.0086)	(.0084)	(.0129)	(.0059)	(.0064)	(.0064)
$d_{it}^{EW,m}(\mathbb{I}_i^E = 1)$	**−.0163*****	**−.0335*****	**−.0468*****	**.3400*****	**.0096*****	−.0008	.0033
	(.0052)	(.0057)	(.0052)	(.0081)	(.0031)	(.0033)	(.0036)
$d_{it}^{WE,m}(\mathbb{I}_i^E = 1)$	.0038	−.0039	−.0015	.0125	−.0057	**−.0095****	−.0023
	(.0066)	(.0072)	(.0067)	(.0085)	(.0042)	(.0045)	(.0050)
$d_{it}^{EW,c}(\mathbb{I}_i^E = 0)$	**−.0088****	**−.0166*****	**−.0138*****	**.0721*****	−.0044	.0048	.0001
	(.0040)	(.0041)	(.0040)	(.0048)	(.0033)	(.0034)	(.0035)
$d_{it}^{WE,c}(\mathbb{I}_i^E = 0)$	−.0017	−.0012	**−.0231*****	**.0454*****	**−.0060***	−.0011	−.0004
	(.0040)	(.0039)	(.0039)	(.0051)	(.0033)	(.0034)	(.0035)
$d_{it}^{EW,c}(\mathbb{I}_i^E = 1)$	**−.0104*****	**−.0240*****	**−.0323*****	**.1485*****	**−.0033***	**−.0043****	**−.0041****
	(.0024)	(.0024)	(.0024)	(.0035)	(.0019)	(.0019)	(.0020)
$d_{it}^{WE,c}(\mathbb{I}_i^E = 1)$	**−.0128*****	**−.0133*****	**−.0190*****	**.0335*****	.0018	.0005	**−.0054****
	(.0026)	(.0027)	(.0028)	(.0035)	(.0021)	(.0021)	(.0022)
$d_{it}^{EE}(\mathbb{I}_i^E = 0)$	**−.0188*****	**−.0200*****	**−.0389*****	**.0712*****	**.0056*****	**.0051****	**.0049****
	(.0025)	(.0026)	(.0025)	(.0031)	(.0021)	(.0021)	(.0023)
$d_{it}^{WW}(\mathbb{I}_i^E = 0)$	**−.0102*****	**−.0186*****	**−.0362*****	**.1247*****	**.0119*****	**.0082*****	**.0070*****
	(.0005)	(.0005)	(.0005)	(.0008)	(.0004)	(.0005)	(.0005)
$d_{it}^{EE}(\mathbb{I}_i^E = 1)$	**−.0134*****	**−.0199*****	**−.0319*****	**.0808*****	**.0034*****	**.0015*****	**.0031*****
	(.0006)	(.0007)	(.0007)	(.0010)	(.0005)	(.0006)	(.0006)
$d_{it}^{WW}(\mathbb{I}_i^E = 1)$	**−.0165*****	**−.0179*****	**−.0332*****	**.1222*****	**.0033*****	.0008	−.0018
	(.0017)	(.0017)	(.0016)	(.0021)	(.0012)	(.0013)	(.0014)
$\mathbb{I}_i^E$	**.0138*****	**.0130*****	**.0141*****	**.0015*****	**−.0015*****	**.0015*****	**.0027*****
	(.0005)	(.0005)	(.0005)	(.0005)	(.0004)	(.0004)	(.0005)
Work_{it}^E	**−.0049*****	**−.0056*****	**−.0028*****	**.0044*****	**.0027*****	**.0047*****	**.0043*****
	(.0006)	(.0006)	(.0006)	(.0007)	(.0006)	(.0006)	(.0006)
$\mathbb{I}_i^E \cdot \text{Work}_{it}^E$	**−.0133*****	**−.0122*****	**−.0166*****	**−.0052*****	.0010	−.0008	**−.0015***
	(.0008)	(.0008)	(.0008)	(.0009)	(.0007)	(.0007)	(.0008)
Year FE	Y	Y	Y	Y	Y	Y	Y
Dist, Switch	Y	Y	Y	Y	Y	Y	Y
Age, Sex, Ed	Y	Y	Y	Y	Y	Y	Y
Obs	7,965,228	8,380,484	8,893,103	8,077,313	6,867,377	5,789,980	4,805,094

Source: LIAB and authors' calculations. Notes: The table presents the estimated coefficients $\beta_{s,\tau}^{West}$ and $\beta_{s,\tau}^{East}$ from regression (2) for the 12 different types of moves, as well as the coefficients of some of the included controls. We omit $t+5$. *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the individual-level. $d_{it}^{jk,l}$ is a dummy that is equal to one if worker i made a job switch of type l from region j to region k at time t, where j and k are either East (E) or West (W), and l is either migration as defined in the main text (m), commuting (c) or within-region (no indicator). $\mathbb{I}_i^E$ is a dummy that is equal to one if the worker's home region is East. Work_{it}^E is a dummy that is equal to one if the worker is currently working in the East. Dist is a set of 5 dummies for the distance of the job-to-job move. Switch is a set of 9 dummies for the number of prior job moves. Age is a set of age dummies for 8 age groups, Sex is a dummy that is one if the worker is male, and Ed is a dummy for whether the worker has a college degree.

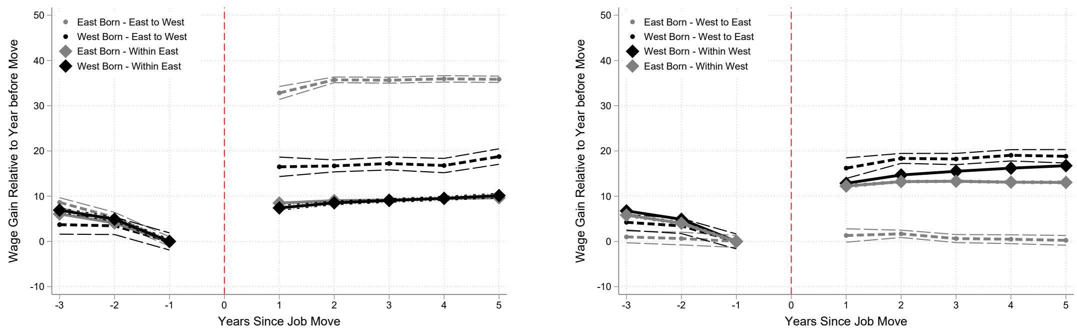
Table S8: Wage Gains of Job-to-Job Moves (With Individual FE)

Dep var.:				Period τ			
$\log(\Delta w_{it})$	t-3	t-2	t-1	t+1	t+2	t+3	t+4
$d_{it}^{EW,m}(\mathbb{I}_i^E=0)$	$-.0095$	$-.0103$	$\mathbf{-.0531}^{***}$	$\mathbf{.1498}^{***}$	$\mathbf{-.0360}^{***}$	$-.0014$	$-.0100$
	(.0126)	(.0122)	(.0122)	(.0136)	(.0093)	(.0099)	(.0111)
$d_{it}^{WE,m}(\mathbb{I}_i^E=0)$	$-.0020$	$-.0063$	$\mathbf{-.0361}^{***}$	$\mathbf{.1434}^{***}$	$-.0109$	$-.0066$	.0057
	(.0109)	(.0100)	(.0109)	(.0137)	(.0078)	(.0087)	(.0091)
$d_{it}^{EW,m}(\mathbb{I}_i^E=1)$	$\mathbf{-.0164}^{**}$	$\mathbf{-.0363}^{***}$	$\mathbf{-.0820}^{***}$	$\mathbf{.2976}^{***}$	$\mathbf{-.0140}^{***}$	$\mathbf{-.0081}^{*}$	.0028
	(.0065)	(.0070)	(.0068)	(.0086)	(.0040)	(.0045)	(.0050)
$d_{it}^{WE,m}(\mathbb{I}_i^E=1)$	.0085	.0046	.0131	$\mathbf{.0223}^{**}$	$-.0081$	$-.0095$	.0005
	(.0079)	(.0087)	(.0082)	(.0094)	(.0054)	(.0062)	(.0072)
$d_{it}^{EW,c}(\mathbb{I}_i^E=0)$	$\mathbf{-.0102}^{**}$	$\mathbf{-.0166}^{***}$	$\mathbf{-.0173}^{***}$	$\mathbf{.0676}^{***}$	$\mathbf{-.0113}^{***}$	.0056	$-.0010$
	(.0048)	(.0049)	(.0048)	(.0055)	(.0042)	(.0044)	(.0048)
$d_{it}^{WE,c}(\mathbb{I}_i^E=0)$	.0009	.0036	$\mathbf{-.0204}^{***}$	$\mathbf{.0442}^{***}$	$\mathbf{-.0140}^{***}$	$-.0030$	$-.0013$
	(.0049)	(.0048)	(.0048)	(.0057)	(.0042)	(.0044)	(.0048)
$d_{it}^{EW,c}(\mathbb{I}_i^E=1)$	$\mathbf{-.0102}^{***}$	$\mathbf{-.0236}^{***}$	$\mathbf{-.0409}^{***}$	$\mathbf{.1397}^{***}$	$\mathbf{-.0088}^{***}$	$\mathbf{-.0062}^{***}$	$\mathbf{-.0049}^{*}$
	(.0028)	(.0029)	(.0029)	(.0039)	(.0024)	(.0024)	(.0027)
$d_{it}^{WE,c}(\mathbb{I}_i^E=1)$	$-.0052$	$\mathbf{-.0062}^{*}$	$\mathbf{-.0119}^{***}$	$\mathbf{.0385}^{***}$	$-.0019$	.0004	$-.0040$
	(.0032)	(.0033)	(.0034)	(.0039)	(.0026)	(.0027)	(.0030)
$d_{it}^{EE}(\mathbb{I}_i^E=0)$	$\mathbf{-.0103}^{***}$	$\mathbf{-.0107}^{***}$	$\mathbf{-.0391}^{***}$	$\mathbf{.0649}^{***}$	.0042	.0014	.0018
	(.0031)	(.0032)	(.0032)	(.0037)	(.0027)	(.0029)	(.0032)
$d_{it}^{WW}(\mathbb{I}_i^E=0)$	$\mathbf{-.0062}^{***}$	$\mathbf{-.0166}^{***}$	$\mathbf{-.0462}^{***}$	$\mathbf{.1020}^{***}$	$\mathbf{.0040}^{***}$	$\mathbf{.0022}^{***}$	$\mathbf{.0040}^{***}$
	(.0006)	(.0006)	(.0006)	(.0009)	(.0006)	(.0006)	(.0006)
$d_{it}^{EE}(\mathbb{I}_i^E=1)$	$\mathbf{-.0064}^{***}$	$\mathbf{-.0135}^{***}$	$\mathbf{-.0342}^{***}$	$\mathbf{.0685}^{***}$	.0005	$\mathbf{-.0013}^{*}$	$\mathbf{.0019}^{**}$
	(.0008)	(.0008)	(.0008)	(.0011)	(.0007)	(.0007)	(.0008)
$d_{it}^{WW}(\mathbb{I}_i^E=1)$	$\mathbf{-.0144}^{***}$	$\mathbf{-.0159}^{***}$	$\mathbf{-.0354}^{***}$	$\mathbf{.1105}^{***}$	$\mathbf{-.0048}^{***}$	$-.0029$	$\mathbf{-.0041}^{**}$
	(.0022)	(.0021)	(.0020)	(.0024)	(.0016)	(.0018)	(.0020)
Work_{it}^E	$\mathbf{-.0124}^{***}$	$\mathbf{-.0172}^{***}$	$\mathbf{-.0159}^{***}$	$\mathbf{.0168}^{***}$	$\mathbf{.0217}^{***}$	$\mathbf{.0121}^{***}$	$\mathbf{.0078}^{**}$
	(.0027)	(.0028)	(.0028)	(.0035)	(.0028)	(.0028)	(.0031)
$\mathbb{I}_i^E \cdot \text{Work}_{it}^E$	.0011	$-.0037$	$\mathbf{-.0235}^{***}$	$\mathbf{.0071}^{*}$	$\mathbf{.0100}^{***}$	$\mathbf{.0079}^{**}$	$-.0003$
	(.0032)	(.0032)	(.0033)	(.0041)	(.0032)	(.0033)	(.0036)
Year FE	Y	Y	Y	Y	Y	Y	Y
Indiv FE	Y	Y	Y	Y	Y	Y	Y
Dist, Switch	Y	Y	Y	Y	Y	Y	Y
Age	Y	Y	Y	Y	Y	Y	Y
Observations	7,965,228	8,380,484	8,893,103	8,077,313	6,867,377	5,789,980	4,805,094

Source: LIAB and authors' calculations. Notes: The table presents the estimated coefficients $\beta_{s,\tau}^{West}$ and $\beta_{s,\tau}^{East}$ from a regression similar to (2) with individual FE for the 12 different types of moves, as well as the coefficients of some of the included controls. We omit $t+5$. *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the individual-level. $d_{it}^{jk,l}$ is a dummy that is equal to one if worker i made a job switch of type l from region j to region k at time t, where j and k are either East (E) or West (W), and l is either migration as defined in the main text (m), commuting (c) or within-region (no indicator). $\mathbb{I}_i^E$ is a dummy that is equal to one if the worker's home region is East. Work_{it}^E is a dummy that is equal to one if the worker is currently working in the East. Dist is a set of 5 dummies for the distance of the job-to-job move. Switch is a set of 9 dummies for the number of past job moves. Age is a set of age dummies for 8 age groups.

Figure S10: Wage Gains for Job-to-Job Moves, Alternative Timing

(a) East-to-West Migration vs. Within-East (b) West-to-East Migration vs. Within-West



Source: LIAB and authors' calculations. Notes: The figure is constructed by taking the point estimates for different sets of coefficients $\beta^{West}_{s,\tau}$ and $\beta^{East}_{s,\tau}$ from the regressions (2) for $\tau \in \{t-3, ..., t-1, t+1, t+5\}$, where in contrast to the main text observations in year t are not dropped but allocated to $t-1$ and $t+1$ as described in the text above. We then sum up the coefficients starting at $\tau = -3$ to obtain for each period τ the sum $\sum_{u=-3}^{\tau} \beta^{i}_{s,u}$, where $i \in \{\text{West, East}\}$, and subtract from this sum the term $\sum_{u=-3}^{-1} \beta^{i}_{s,u}$ to normalize the coefficients with respect to period $\tau = -1$. The dotted lines represent the 95% confidence intervals. The dashed lines in the left panel show the normalized coefficients for $\beta^{West}_{EW,\tau}$ and $\beta^{East}_{EW,\tau}$, and the solid lines with diamonds show $\beta^{East}_{EE,\tau}$ and $\beta^{West}_{EE,\tau}$. The dashed lines in the right panel show the normalized coefficients for $\beta^{West}_{WE,\tau}$ and $\beta^{East}_{WE,\tau}$, and the solid lines with diamonds show $\beta^{West}_{WW,\tau}$ and $\beta^{East}_{WW,\tau}$.

Table S9: Wage Gains Robustness

Dep var.: $\Delta \log(w_{it})$	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Month gap	$\leq$ 2 mths	$\leq$ 200km	$\leq$ 350km	Any move
$d_{it}^{EW,m}(\mathbb{I}_i^{East}=0)$	**.1809***	**.0817***	**.0674***	**.1675***	**.1561***	**.1041***
	(.0181)	(.0175)	(.0169)	(.0134)	(.0119)	(.0092)
$d_{it}^{WE,m}(\mathbb{I}_i^{East}=0)$	**.2034***	.0274	−.0125	**.1803***	**.1822***	**.1380***
	(.0193)	(.0182)	(.0150)	(.0140)	(.0144)	(.0111)
$d_{it}^{EW,m}(\mathbb{I}_i^{East}=1)$	**.3268***	**.1798***	**.1071***	**.2645***	**.2227***	**.1927***
	(.0119)	(.0110)	(.0092)	(.0079)	(.0063)	(.0062)
$d_{it}^{WE,m}(\mathbb{I}_i^{East}=1)$	**.0384***	**−.0495***	**−.0321***	**.0412***	**.0538***	**.0683***
	(.0108)	(.0107)	.0100	(.0101)	(.0117)	(.0075)
$d_{it}^{EW,c}(\mathbb{I}_i^{East}=0)$	**.0839***	.0148	.0105	**.0707***	**.0685***	
	(.0103)	(.0102)	(.0116)	(.0114)	(.0123)	
$d_{it}^{WE,c}(\mathbb{I}_i^{East}=0)$	**.1165***	**.0399***	**.0515***	**.1053***	**.0763***	
	(.0133)	(.0133)	(.0154)	(.0158)	(.0165)	
$d_{it}^{EW,c}(\mathbb{I}_i^{East}=1)$	**.1429***	**.0688***	**.0555***	**.1202***	**.1088***	
	(.0066)	(.0064)	(.0069)	(.0084)	(.0126)	
$d_{it}^{WE,c}(\mathbb{I}_i^{East}=1)$	**.0759***	.0040	**.0271***	**.0722***	**.0713***	
	(.0087)	(.0087)	(.0102)	(.0090)	(.0089)	
$\mathbb{I}_i^{East}$	**−.0036***	−.0019	.0015	**−.0037***	**−.0037***	**−.0037***
	(.0013)	(.0013)	(.0012)	(.0013)	(.0013)	(.0013)
Work_{it}^{East}	.0025	.0027	**.0032***	.0025	.0025	.0025
	(.0018)	(.0018)	(.0017)	(.0018)	(.0018)	(.0018)
$\mathbb{I}_i^{East} \cdot \text{Work}_{it}^{East}$	.0028	.0003	−.0024	.0028	.0028	.0028
	(.0022)	(.0022)	(.0021)	(.0022)	(.0022)	(.0022)
Year FE	Y	Y	Y	Y	Y	Y
Dist, Switch	Y	Y	Y	Y	Y	Y
Age, Sex, Ed	Y	Y	Y	Y	Y	Y
Observations	5,545,110	5,545,110	5,545,110	5,545,110	5,545,110	5,545,110

Source: LIAB and authors' calculations. Notes: The table presents the estimates of selected coefficients of specification (38), with various robustness checks. The coefficients for within-region moves are omitted for brevity. $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the individual level. $\mathbb{I}_i^{East}$ is a dummy that is equal to one if the worker's home region is East. Work_{it}^{East} is a dummy that is equal to one if the worker is currently working in the East. Dist is a set of 5 dummies for the distance of the job-to-job move. Switch is a set of 9 dummies for the number of past job moves. Age is a set of age dummies for 8 age groups, Sex is a dummy that is one if the worker is male, and Ed is a dummy for whether the worker has a college degree. Column (1) presents the benchmark regression (38). Migration (m) is defined as a job change between East and West Germany that entails a change in the residence county in the year of the move compared to the previous year. All other cross-area moves are commuting (c). Column (2) adds to the benchmark regression a control for the number of months between job spells. Column (3) drops all job switches where more than two months elapse between jobs. Column (4) expands the definition of cross-area migration to also include all moves that increase the distance to the residence county, as long as the distance between work and residence is less than 200km. Column (5) increases the distance threshold between work and residence to 350km. Column (6) classifies all job switches out of the current region to the other region as migration.

Table S10: Wage Gains for Sub Groups

Dep var.:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta\log(w_{it})$	Male	Female	College	No coll.	Young	Middle	Older
$d_{it}^{EW,m}(\mathbb{I}_i^E=0)$	**.1632*****	**.2118*****	**.2329*****	**.1723*****	**.2294*****	**.1450*****	**.0986*****
	(.0210)	(.0348)	(.0317)	(.0262)	(.0257)	(.0312)	(.0325)
$d_{it}^{WE,m}(\mathbb{I}_i^E=0)$	**.1625*****	**.2778*****	**.4010*****	**.0611****	**.3187*****	**.0520***	$-.0598$
	(.0226)	(.0362)	(.0366)	(.0259)	(.0265)	(.0284)	(.0377)
$d_{it}^{EW,m}(\mathbb{I}_i^E=1)$	**.2871*****	**.3913*****	**.5182*****	**.2855*****	**.3745*****	**.1520*****	**.1209*****
	(.0128)	(.0240)	(.0313)	(.0143)	(.0140)	(.0221)	(.0219)
$d_{it}^{WE,m}(\mathbb{I}_i^E=1)$	**.0259****	**.0552*****	**.1760*****	$-.0157$	**.0626*****	.0210	$-.0499$
	(.0129)	(.0195)	(.0258)	(.0132)	(.0123)	(.0271)	(.0333)
$d_{it}^{EW,c}(\mathbb{I}_i^E=0)$	**.0729*****	**.0948*****	**.1687*****	**.1095*****	**.1664*****	**.0337***	.0038
	(.0110)	(.0250)	(.0198)	(.0111)	(.0148)	(.0186)	(.0219)
$d_{it}^{WE,c}(\mathbb{I}_i^E=0)$	**.0874*****	**.2013*****	**.1877*****	**.0717*****	**.1957*****	**.0839*****	.0261
	(.0151)	(.0266)	(.0260)	(.0117)	(.0155)	(.0278)	(.0254)
$d_{it}^{EW,c}(\mathbb{I}_i^E=1)$	**.1259*****	**.1745*****	**.2352*****	**.1406*****	**.2087*****	**.1046*****	**.0230***
	(.0076)	(.0133)	(.0243)	(.0073)	(.0093)	(.0107)	(.0133)
$d_{it}^{WE,c}(\mathbb{I}_i^E=1)$	**.0531*****	**.1330*****	**.1448*****	**.0452*****	**.1058*****	**.0460*****	.0445
	(.0085)	(.0268)	(.0163)	(.0073)	(.0088)	(.0120)	(.0278)
$\mathbb{I}_i^E$	**−.0046*****	$-.0004$	$-.0003$	**−.0082*****	**−.0036****	.0010	.0030
	(.0015)	(.0023)	(.0022)	(.0013)	(.0015)	(.0033)	(.0025)
Work_{it}^E	.0010	.0076	.0035	**.0048*****	$-.0019$	.0036	.0030
	(.0018)	(.0047)	(.0031)	(.0017)	(.0037)	(.0031)	(.0025)
$\mathbb{I}_i^{East}\cdot\text{Work}_{it}^E$	.0011	.0027	.0050	**.0040***	.0066	**−.0085***	$-.0012$
	(.0023)	(.0052)	(.0039)	(.0022)	(.0041)	(.0045)	(.0036)
DiD Migr	.2605	.4021	.5103	.1900	.4012	.0380	.0124
DiD Comm	.0873	.1480	.1094	.0576	.1322	.1088	.0008
Year FE	Y	Y	Y	Y	Y	Y	Y
Dist, Switch	Y	Y	Y	Y	Y	Y	Y
Age, Sex, Ed	Y	Y	Y	Y	Y	Y	Y
Observations	4,013,950	1,531,160	851,400	3,277,109	2,144,040	1,491,931	1,909,139

Source: LIAB and authors' calculations. Notes: The table presents the estimates of selected coefficients of specification (38), for various sub groups of the population. The coefficients for within-region moves are omitted for brevity. $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the individual level. $\mathbb{I}_i^E$ is a dummy that is equal to one if the worker's home region is East. Work_{it}^E is a dummy that is equal to one if the worker is currently working in the East. Dist is a set of 5 dummies for the distance of the job-to-job move. Switch is a set of 9 dummies for the number of past job moves. Age is a set of age dummies for 8 age groups, Sex is a dummy that is one if the worker is male, and Ed is a dummy for whether the worker has a college degree. High-skilled workers are workers with a college degree. Young workers were born from 1975 onwards. Middle-aged workers were born 1965-1974. Older workers were born before 1965. The rows "DiD Migr" and "DiD Comm" verify the presence of home bias, and are calculated as $(d_{it}^{EW,m}(\mathbb{I}_i^{East}=1)-d_{it}^{WE,m}(\mathbb{I}_i^{East}=1))-(d_{it}^{EW,m}(\mathbb{I}_i^{East}=0)-d_{it}^{WE,m}(\mathbb{I}_i^{East}=0))$ for migrants, and analogously for commuters. A positive value indicates that the difference in the wage gain moving out of the East compared to returning is larger for East Germans than for West Germans, i.e., home bias.

N Additional Statistics on Worker Mobility

In this section, we present some additional statistics on worker mobility.

Summary Statistics for Migrants. Table S11 presents statistics similar to Table 1, but considers only migrants as opposed to all movers. Since migration can only be identified since 1999 due to the lack of residence data before then, the migration statistics are computed for this shorter period. To make the numbers comparable to those for all movers, Table S12 presents the table for all movers, as in the main text, using only their employment history since 1999. Comparing Table S11 and Table S12, we find that the share of workers that migrate away from their home region is significantly smaller than the share of workers that take up a job in the other region. However, conditional on migrating, migrants are considerably less likely to return home than all movers. Moreover, West German migrants that return home spend on average a longer time in the East before moving back than all West German movers. We do not find such a difference for East German migrants.

The bottom panels of Table S11 and S12 show some characteristics of stayers, movers, and movers that return home. We find that the share of college-educated migrants is significantly higher than the share of college-educated movers overall. West German migrants and movers are significantly more likely to be college-educated than East German migrants and movers. Considering the gender of migrants, we find that the male share among migrants is comparable to the male share among non-migrants for both East and West Germans. However, East German movers overall are significantly more likely to be male than stayers.

Distribution of Cross-Border Moves. Table S13 shows the distribution of the number of cross-border moves for workers with at least one full-time employment spell in our core sample in 2009-2014, using these workers' employment history for as many years as possible. Columns 1-2 present all cross-border moves, i.e., the number of times a worker switched full-time jobs to the other region. While the vast majority of West German workers move across regions at most three times, a small number of East German workers move up to six times. Columns 3-4 count cross-border moves since 1999 only. Columns 5-6 present the number of job-to-job migration moves. These moves are significantly rarer than general moves across regions by definition, with the majority of migrants moving only once. Columns 7-8 present the distribution for moves under the intermediate definition, as defined in Appendix B.

Mobility by Cohort. Table S14 looks at different cohorts of workers based on when they first took a full-time job outside of their home region, using all movers. As expected, we find that a higher share of workers returned home in the cohort that moved outside of their home region earlier. However, even in the later cohort about one third of workers that have moved away have since taken up a job in their home region. East Germans were significantly more likely to return home than West Germans in the earlier cohort, but not in the later one.

Table S11: Summary Statistics for Migrants

			(1)			(2)	
			Home: West			Home: East	
(1)	Crossed border		0.9%			3.9%	
(2)	Returned movers		30.1%			15.8%	
(3)	Mean years away (returners)		2.27			2.31	
(4)	Mean years away (non-returners)		4.67			5.16	
		Stayers	Movers	Returners	Stayers	Movers	Returners
(5)	Age at first move	–	33.5	33.2	–	30.6	29.5
(6)	Share college	0.22	0.50	0.51	0.20	0.32	0.30
(7)	Share male	0.70	0.67	0.73	0.60	0.61	0.69

Source: LIAB. Notes: The table shows statistics for workers with at least one full-time employment spell in our core sample period 2009-2014. Row 1 shows the share of these workers that have ever migrated to their non-home region, over the sample since 1999 since we do not have residence information prior to that year. Migration is defined as a job switch to the non-home region associated with a change in the county of residence in the year of the job move. Row 2 shows the share of workers that have ever taken up a job again in their home region after their first migration to the non-home region. Row 3 presents the average number of years passed between the first migration to the non-home region and the worker's job back home for returners. Row 4 shows the time passed between the last year the worker is in the data and the year of the first migration out of the home region for workers that never again take a job in their home region. Rows (5)-(7) present the average age at the migration move away from home, college share, and male share among workers that have never migrated out of their home region ("Stayers"), workers that have migrated ("Movers"), and workers that have migrated and returned to a job ("Returners").

Table S12: Summary Statistics for Job Moves since 1999

		(1) Home: West			(2) Home: East		
(1)	Crossed border		3.8%			21.9%	
(2)	Returned movers		41.9%			32.3%	
(3)	Mean years away (returners)		1.86			2.34	
(4)	Mean years away (non-returners)		5.38			6.65	
		Stayers	Movers	Returners	Stayers	Movers	Returners
(5)	Age at first move	–	35.9	35.5	–	32.3	32.2
(6)	Share college	0.22	0.34	0.32	0.19	0.19	0.19
(7)	Share male	0.70	0.75	0.80	0.57	0.73	0.78

Source: LIAB. Notes: The table shows statistics for workers with at least one full-time employment spell in our core sample period 2009-2014, and considers their employment history since 1999 only. Row 1 shows the share of these workers that have ever worked in their non-home region, over the sample since 1999. Row 2 shows the share of workers that returned to a job in their home region after their first job in the non-home region. Row 3 presents the average number of years passed between the first job in the non-home region and the worker's return to a job at home for returners. Row 4 shows the time passed between the last year the worker is in the data and the year of the first job outside of the home region for workers that never again take a job in their home region. Rows (5)-(7) present the average age at the first move away from the home region, college share, and male share among workers that have never taken a job outside of their home region ("Stayers"), workers that have moved ("Movers"), and workers that have moved away and returned to a job in the home region ("Returners").

Table S13: Distribution of Cross-Region Moves Throughout Workers' Lifetime

	Share of Workers Throughout Lifetime							
Number of cross-border moves	All Movers		All Movers 99		Migration		Intermediate	
Time period	1993-2014		1999-2014		1999-2014		1999-2014	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Home:	West	East	West	East	West	East	West	East
0	95.4%	76.1%	96.2%	78.1%	99.1%	96.1%	98.7%	93.8%
...1	2.3%	13.0%	1.9%	12.5%	0.7%	3.5%	1.1%	5.4%
...2 – 3	1.9%	8.6%	1.6%	7.6%	0.2%	0.4%	0.3%	0.8%
...4 – 6	0.4%	1.8%	0.3%	1.5%	0.0%	0.0%	0.0%	0.0%
...7+	0.1%	0.4%	0.1%	0.3%	0.0%	0.0%	0.0%	0.0%

Source: LIAB. Notes: The table shows statistics for workers with at least one employment spell in our core sample period 2009-2014. For these workers, we compute the distribution of the number of cross-region moves throughout their lifetime, going back as many years as available. The first two columns present the number of times workers take up a job in the region different from the region of their last job since 1993. Columns 3-4 show the same distribution of moves but counting only moves since 1999. Columns 5-6 present the distribution of migration job-to-job moves between East and West Germany since 1999. Columns 7-8 present the number of job-to-job moves based on our intermediate definition since 1999. The intermediate definition includes migration moves plus other cross-region moves that increase the distance to the residence county, as long as the distance from the work county to the residence does not exceed 200km, as described in the text.

Table S14: Mobility by Cohort

	(1)	(2)	(3)	(4)
	Movers before 1996		Movers after 2004	
	Home: West	Home: East	Home: West	Home: East
Returned movers	52.0%	71.2%	39.6%	29.6%
Mean years away (returners)	5.58	2.55	1.41	1.66
Mean years away (non-returners)	19.29	19.08	3.34	4.02

Source: LIAB. Notes: The table shows statistics for our cleaned data for 1993-2014 for workers with at least one employment spell in our core sample period 2009-2014, but distinguishes between two cohorts: workers that took the first job outside of their home region prior to 1996 (columns 1-2) and workers that first took a job outside of their home region after 2004 (columns 3-4). Row 1 presents the share of workers, among these movers, that have since moved back to a job in their home region. Row 2 presents the average number of years passed between the first job in the non-home region and the worker's return home for returners. Row 3 shows the time passed between the last year the worker is in the data and the year of the first job outside of the home region for workers that never again take a job in their home region.

O Additional Results on Workers' Flows

Baseline Regression. Column 1 of Table S15 presents the estimated coefficients from our gravity specification (3). We find that the distance coefficients, ϕ_x, decline with distance, consistent with workers being less likely to move between counties further apart. The coefficient on the cross-border term, $\mathbb{I}_{(R(o)\neq R(d))}$, should be negative if workers are less likely to move across the East-West border regardless of their home region or distance. The estimated coefficient is marginally positive, indicating that there is no cross-border effect after controlling for distance and fixed effects. As discussed in the main text, we find significantly different destination fixed effects for workers with different home regions.

Origin Fixed Effects. Figure S11 plots the difference of the origin fixed effects between East and West Germans, $\delta_o^{East} - \delta_o^{West}$, for each county against the distance of that county to the East-West border, analogous to Figure 3b, which showed the destination fixed effects. Counties in East Germany exhibit a negative difference in fixed effects between East- and West-born workers, indicating that East-born workers are less likely to move away from these counties. The difference is slightly smaller for counties closer to the border, but there is still a strong discontinuity.

Robustness. Columns 2-6 of Table S15 show a number of robustness checks of our main gravity specification. To summarize the effect of workers' home region, we replace the origin-home region and destination-home region fixed effects in these regressions with simple origin and destination fixed effects by running

$$\log s^h_{o,d} = \delta_o + \gamma_d + \sum_{x \in \mathbb{X}} \phi_x D_{x,o,d} + \rho \mathbb{I}_{R(o) \neq R(d)} + \beta_1 \mathbb{I}^{East} + \beta_2 \mathbb{I}_{(R(o)=h)} + \beta_3 \mathbb{I}_{(R(d)=h)} + \epsilon^h_{o,d}. \quad (39)$$

In this specification, we add a dummy for whether the origin county was in the worker's home region, $\mathbb{I}_{(R(o)=h)}$, and a dummy for whether the destination county was in the worker's home region, $\mathbb{I}_{(R(d)=h)}$. If worker flows are biased towards workers' home region, the coefficient on the origin home dummy will be negative and the coefficient on the destination home dummy will be positive, indicating relatively fewer flows out of the home region and more flows into the home region. We also add a dummy for East German workers, $\mathbb{I}^{East}$. Column 2 runs this specification on our dataset. The results are similar to our main specification. In particular, we find a large and negative coefficient on the origin home dummy and a large and positive coefficient on the destination home dummy, indicating significant home bias.

Column 3 re-runs this specification but keeps only job changes across counties that are associated with a change in the residence county in the year of the job switch compared to one year prior ("migration across counties"). Restricting the sample to only such moves significantly reduces the number of origin-destination county pairs for which we see flows. We find a smaller but still very significant negative effect of distance and still significant home bias. In particular, workers are significantly less likely to move across counties if their origin county is in their home region.

Column 4 adds to the migration moves of Column 3 those moves where the worker changes jobs between counties without a change in residence, as long as the new job is further away from the worker's residence than the old one and the distance between work and residence is less than 200km for both jobs. We impose this threshold since a distance greater than 200km between residence and work likely indicates that the residence is misreported. In Column 5, we further broaden this definition and increase the threshold between work and residence from 200km to 350km. These changes strengthen the home bias we find relative to the regression with only migration moves. Finally, in Column 6, we return to the baseline definition of all job-to-job moves and add to these all job changes with an intermittent spell of unemployment. Adding these moves increases the number of county pairs for which we observe flows. The results are very similar to the regression with only job-to-job movers in Column 2.

Demographic Groups. In Table S16, we next run specification (39) for different sub groups of the population. Columns 1 and 2 contain the results for male and female workers, respectively. In Columns 3 and 4, we analyze workers with and without a college degree. In Columns 5 to 7, we examine the results for workers of different age groups. While the number of county pairs for which we observe flows drops in these specifications, the results are overall very similar and indicate substantial home bias for all groups.

Flexible Specification for Cross-Region Moves. Column 1 of Table S17 runs specification (39) but replaces the dummy for moves across regions, $\mathbb{I}_{(R(o) \neq R(d))}$, with a more flexible specification that controls for the distance between the origin county and the former East-West border. Specifically, we run

$$\log s_{o,d}^h = \delta_o + \gamma_d + \sum_{x \in \mathbb{X}} \phi_x D_{x,o,d} + \xi_{o,d} \sum_{y \in \mathbb{Y}} \psi_y D_{y,o} + \beta_1 \mathbb{I}^{East} + \beta_2 \mathbb{I}_{(R(o)=h)} + \beta_3 \mathbb{I}_{(R(d)=h)} + \epsilon_{o,d}^h, \quad (40)$$

where $\xi_{o,d}$ is a dummy that is equal to one if the origin and destination county are in different regions, and $D_{y,o}$ are dummies for buckets of the distance between the origin county and the East-West border. The set of buckets $\mathbb{Y}$ contains the intervals 1km-99km, 100-149km, 150-199km, and more than 199km. This specification analyzes whether workers that are further away from the border have a stronger resistance towards moving across regions. Column 1 shows that workers are actually slightly more likely to cross the former border if their origin county is further away, but the effect is small. We still find significant home bias as before.

Regions and Locations. Column 2 further divides each of East and West Germany into two "locations", so that overall we have four locations: Northwest (NW), Southwest (SW), Northeast (NE), and Southeast (SE). These four locations are the same as the ones used in our estimation section. We then estimate

$$\log s_{o,d}^h = \delta_o + \gamma_d + \sum_{x \in \mathbb{X}} \phi_x D_{x,o,d} + \sum_{h \in \mathbb{H}} \beta_h \mathbb{I}^h + \sum_{k \in \mathbb{K}} \beta_k \mathbb{I}_k + \sum_{m \in \mathbb{M}} \gamma_m \mathbb{I}_m + \epsilon_{o,d}^h, \quad (41)$$

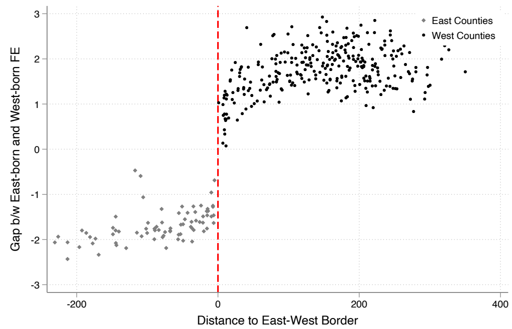
where $\mathbb{I}^h$ is a set of dummies for the worker's home location, $\mathbb{H} = \{SW, NE, SE\}$, and the dummies $\mathbb{I}_k$ capture moves between East and West Germany in the same way as before, with $\mathbb{K} = \{R(o) \neq R(d), R(o) = h, R(d) = h\}$. We also define $\mathbb{M} = \{L(o) \neq L(d), L(o) = h, L(d) = h\}$, where $\mathbb{I}_{L(o) \neq L(d)}$ is equal to one for moves between any of the four locations, $L(o) = h$ is equal to one if the origin county is in the location that is the worker's home, and $L(d) = h$ is equal to one if the destination county is in the location that is the worker's home. By including both the dummies for moves between East and West Germany and the dummies for moves between the finer locations, we can distinguish the effects of moving between East and West from the effects of moving between the locations. Column 2 shows that there is substantial attachment to workers' location. However, we also find a significant, though smaller, home bias towards the larger overall region.

Table S15: Gravity Regression - Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Different FE	County migration	Migration <= 200km	Migration <= 350km	Unemp
$\mathbb{I}_{(R(o)\neq R(d))}$	**.0373***	**.0316***	**.0414***	**.0249**	**.0243**	**.0250***
	(.0088)	(.0091)	(.0103)	(.0120)	(.0110)	(.0081)
ϕ_{50-99}	**−1.6989***	**−1.7226***	**−.9277***	**−1.6616***	**−1.6528***	**−1.8248***
	(.0189)	(.0189)	(.0167)	(.0205)	(.0204)	(.0188)
$\phi_{100-149}$	**−2.3712***	**−2.4002***	**−1.2299***	**−2.2460***	**−2.2279***	**−2.5658***
	(.0188)	(.0188)	(.0170)	(.0208)	(.0206)	(.0185)
$\phi_{150-199}$	**−2.5993***	**−2.6178***	**−1.3405***	**−2.4368***	**−2.4079***	**−2.8291***
	(.0188)	(.0188)	(.0172)	(.0210)	(.0207)	(.0185)
$\phi_{200-249}$	**−2.6974***	**−2.7081***	**−1.3816***	**−2.6521***	**−2.4839***	**−2.9406***
	(.0189)	(.0190)	(.0173)	(.0218)	(.0209)	(.0186)
$\phi_{250-299}$	**−2.7471***	**−2.7565***	**−1.3938***	**−2.6779***	**−2.5084***	**−2.9984***
	(.0192)	(.0192)	(.0177)	(.0223)	(.0212)	(.0187)
$\phi_{300-349}$	**−2.7799***	**−2.7895***	**−1.4041***	**−2.7046***	**−2.5497***	**−3.0349***
	(.0195)	(.0195)	(.0185)	(.0230)	(.0217)	(.0190)
$\phi_{350-399}$	**−2.8307***	**−2.8324***	**−1.4460***	**−2.7415***	**−2.7117***	**−3.0854***
	(.0197)	(.0198)	(.0187)	(.0235)	(.0228)	(.0192)
ϕ_{400+}	**−2.9105***	**−2.9049***	**−1.4879***	**−2.7903***	**−2.7882***	**−3.1686***
	(.0193)	(.0192)	(.0177)	(.0223)	(.0219)	(.0187)
$\mathbb{I}^{East}$		**.1699***	**.1100***	**.1086***	**.1085***	**.1560***
		(.0082)	(.0096)	(.0115)	(.0105)	(.0072)
$\mathbb{I}_{(R(o)=h)}$		**−1.6683***	**−1.4113***	**−1.9058***	**−1.8403***	**−1.6264***
		(.0074)	(.0087)	(.0100)	(.0091)	(.0065)
$\mathbb{I}_{(R(d)=h)}$		**.5505***	**.2854***	**.4325***	**.3819***	**.5979***
		(.0075)	(.0087)	(.0102)	(.0095)	(.0065)
Origin-home FE	Y	–	–	–	–	–
Destination-home FE	Y	–	–	–	–	–
Origin FE	–	Y	Y	Y	Y	Y
Destination FE	–	Y	Y	Y	Y	Y
Observations	75,937	75,937	37,246	46,978	53,714	95,275

Source: LIAB and authors' calculations. Notes: The table presents robustness checks of specification (3). Column 1 presents the estimated coefficients from the baseline equation. $\mathbb{I}_{(R(o)\neq R(d))}$ is a dummy that is equal to one if the job switch is between regions, i.e., between East and West Germany. The coefficients ϕ_x are dummies for the distance of the move, where the set of buckets $\mathbb{X}$ contains 50km intervals from 50km-99km onward to 350km-399km, and an eighth group for counties that are further than 399 km apart. Column 2 replaces the origin-by-home region and destination-by-home region fixed effects with origin and destination fixed effects, and includes three additional dummies: $\mathbb{I}^{East}$ is a dummy that is equal to one for workers whose home region is East Germany, $\mathbb{I}_{(R(o)=h)}$ is a dummy that is equal to one for workers whose job prior to the job-to-job move was in their home region, and $\mathbb{I}_{(R(d)=h)}$ is a dummy that is equal to one for workers whose job after to the switch is in their home region. Column 3 includes only cases where the job switch is accompanied by a change in residence county. Column 4 expands this to also include all moves that increase the distance to the residence county, as long as the distance between work and residence is less than 200km. Column 5 increases the distance threshold between work and residence to 350km. Column 6 includes not only job-to-job moves but also all job changes with an intermittent unemployment spell.

Figure S11: Origin Fixed Effects



Source: LIAB and authors' calculations. Notes: The figure plots the difference between the origin fixed effects for East- and West-born, $\delta_o^{East} - \delta_o^{West}$ from the baseline gravity regression (3), as a function of the distance of each county o to the East-West former border. We normalize the fixed effect coefficients for each worker type by their mean and plot counties in the East with a negative distance.

Table S16: Gravity Regression - Sub-Groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Males	Females	College	No coll.	Young	Middle	Older
$\mathbb{I}_{(R(o)\neq R(d))}$	**.0430*****	$-.0029$	$-.0208$	**.0630*****	**.0869*****	.0126	$-.0082$
	(.0095)	(.0139)	(.0139)	(.0109)	(.0104)	(.0129)	(.0143)
ϕ_{50-99}	**−1.6265*****	**−1.4747*****	**−1.0522*****	**−1.6746*****	**−1.5994*****	**−1.4074*****	**−1.3376*****
	(.0191)	(.0205)	(.0202)	(.0199)	(.0189)	(.0204)	(.0225)
$\phi_{100-149}$	**−2.2441*****	**−1.9595*****	**−1.4153*****	**−2.2691*****	**−2.2037*****	**−1.8347*****	**−1.7457*****
	(.0191)	(.0215)	(.0209)	(.0202)	(.0191)	(.0213)	(.0234)
$\phi_{150-199}$	**−2.4342*****	**−2.0871*****	**−1.5056*****	**−2.4374*****	**−2.3791*****	**−1.9345*****	**−1.8531*****
	(.0192)	(.0219)	(.0213)	(.0204)	(.0192)	(.0216)	(.0240)
$\phi_{200-249}$	**−2.5080*****	**−2.1460*****	**−1.5588*****	**−2.4901*****	**−2.4520*****	**−1.9638*****	**−1.8549*****
	(.0194)	(.0225)	(.0217)	(.0207)	(.0195)	(.0217)	(.0240)
$\phi_{250-299}$	**−2.5512*****	**−2.1659*****	**−1.5776*****	**−2.5270*****	**−2.4881*****	**−1.9980*****	**−1.8879*****
	(.0196)	(.0230)	(.0224)	(.0210)	(.0198)	(.0224)	(.0245)
$\phi_{300-349}$	**−2.5833*****	**−2.1507*****	**−1.5944*****	**−2.5482*****	**−2.5183*****	**−1.9847*****	**−1.8634*****
	(.0200)	(.0239)	(.0235)	(.0215)	(.0202)	(.0233)	(.0260)
$\phi_{350-399}$	**−2.6204*****	**−2.1988*****	**−1.6246*****	**−2.5675*****	**−2.5480*****	**−2.0246*****	**−1.9016*****
	(.0203)	(.0244)	(.0240)	(.0218)	(.0207)	(.0244)	(.0259)
ϕ_{400+}	**−2.6794*****	**−2.2250*****	**−1.6743*****	**−2.6179*****	**−2.5962*****	**−2.0701*****	**−1.9118*****
	(.0197)	(.0228)	(.0223)	(.0211)	(.0198)	(.0225)	.0249)
$\mathbb{I}^{East}$	**.1980*****	**−.0229***	**.2402*****	**.0797*****	$-.0119$	**.4031*****	**.1800*****
	(.0087)	(.0136)	(.0130)	(.0104)	(.0102)	(.0122)	(.0133)
$\mathbb{I}_{(R(o)=h)}$	**−1.6647*****	**−1.8374*****	**−1.6666*****	**−1.7893*****	**−1.7728*****	**−1.6813*****	**−1.8975*****
	(.0079)	(.0124)	(.0118)	(.0093)	(.0091)	(.0111)	(.0123)
$\mathbb{I}_{(R(d)=h)}$	**.5128*****	**.4179*****	**.3385*****	**.4949*****	**.5359*****	**.3679*****	**.3792*****
	(.0080)	(.0120)	(.0120)	(.0093)	(.0088)	(.0113)	(.0124)
Origin FE	Y	Y	Y	Y	Y	Y	Y
Destination FE	Y	Y	Y	Y	Y	Y	Y
Observations	65,478	32,956	28,727	50,275	56,349	31,410	28,110

Source: LIAB and authors' calculations. Notes: The table presents gravity estimates for sub groups of the population. *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. $\mathbb{I}_{(R(o)\neq R(d))}$ is a dummy that is equal to one if the job switch is between regions, i.e., between East and West Germany. The coefficients ϕ_x are dummies for the distance of the move, where the set of buckets $\mathbb{X}$ contains 50km intervals from 50km-99km onward to 350km-399km, and an eighth group for counties that are further than 399 km apart. $\mathbb{I}^{East}$ is a dummy that is equal to one for workers whose home region is East Germany, $\mathbb{I}_{(R(o)=h)}$ is a dummy that is equal to one for workers whose job prior to the job-to-job move was in their home region, and $\mathbb{I}_{(R(d)=h)}$ is a dummy that is equal to one for workers whose job after to the switch is in their home region. Columns 1 and 2 present the estimates for the samples of only males and only females, respectively. Columns 3 and 4 consider workers with a college education and without a college education, respectively. Young workers were born from 1975 onwards. Middle-aged workers were born 1965-1974. Older workers were born before 1965.

Table S17: Gravity Regression - Robustness II

	(1)	(2)
	Flexible Distance	Cross Location
ψ_{1-99}	$\mathbf{-.0490}^{***}$	
	(.0118)	
$\psi_{100-149}$	$\mathbf{.0792}^{***}$	
	(.0168)	
$\psi_{150-199}$	$\mathbf{.1409}^{***}$	
	(.0171)	
ψ_{200+}	$\mathbf{.1672}^{***}$	
	(.0173)	
$\mathbb{I}_{(R(o)=h)}$	$\mathbf{-1.6669}^{***}$	$\mathbf{-.3495}^{***}$
	(.0074)	(.0090)
$\mathbb{I}_{(R(d)=h)}$	$\mathbf{.5505}^{***}$	$\mathbf{.1293}^{***}$
	(.0075)	(.0088)
$\mathbb{I}_{(R(o)\neq R(d))}$		$\mathbf{-.1270}^{***}$
		(.0091)
$\mathbb{I}_{(L(o)=h)}$		$\mathbf{-1.8252}^{***}$
		(.0076)
$\mathbb{I}_{(L(d)=h)}$		$\mathbf{.5069}^{***}$
		(.0075)
$\mathbb{I}_{(L(o)\neq L(d))}$		$\mathbf{.0712}^{***}$
		(.0087)
Distance	Y	Y
Home Region FE	Y	–
Home Location FE	–	Y
Origin FE	Y	Y
Destination FE	Y	Y
Observations	$75,937$	$92,512$

Source: LIAB and authors' calculations. Notes: The first column presents the estimated coefficients for specification (40). We omit the distance coefficients ϕ_x, the East home region dummy $\mathbb{I}^{East}$ (from column (1)), and the three home location dummies $\mathbb{I}^h$ (from column (2)) for brevity. *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. The coefficients ψ_y are dummies for buckets of the distance between the origin county and the East-West border. The set of buckets $\mathbb{Y}$ contains the intervals 1km-99km, 100-149km, 150-199km, and more than 199km. $\mathbb{I}_{(R(o)=h)}$ is a dummy that is equal to one for workers whose job prior to the job-to-job move was in their home region, and $\mathbb{I}_{(R(d)=h)}$ is a dummy that is equal to one for workers whose job after to the switch is in their home region. The second column presents the estimated coefficients for specification (41). $\mathbb{I}_{(R(o)\neq R(d))}$ is a dummy that is equal to one if the job switch is between regions, i.e., between East and West Germany. $\mathbb{I}_{(L(o)\neq L(d))}$ is a dummy that is equal to one if the job switch is between locations, such as NW and SE. $\mathbb{I}_{(L(o)=h)}$ is a dummy that is equal to one for workers whose job prior to the job-to-job move was in their home location, and $\mathbb{I}_{(L(d)=h)}$ is a dummy that is equal to one for workers whose job after to the switch is in their home location.

P Comparison to the Burdett-Mortensen Model

Lemma 1. *If $a^i_{jx}(s_x) = 1$ and $\kappa^i_{jx} = 0$ for all i, j, and x, $\theta^i_j = 1$, $\tau^i_j = \tau_j$, $\delta^i_j = \delta$, $b^i_j\tau^i_jP_j^{-1} = \hat{b}$, and $R^i_j\tau^i_jP_j^{-1} = \hat{R}$ for all i and j, $\nu = 1$, $\chi = 0$, and $\sigma \to 0$, then the ODEs for the wage functions simplify to*

$$\frac{\partial \hat{w}(p)}{\partial p} = \frac{-2\left(p - \hat{w}(p)\right)\frac{\partial \tilde{q}(p)}{\partial p}}{\tilde{q}(p)}$$

where

$$\tilde{q}(p) = \delta + \bar{v}[1 - \tilde{F}(p)]$$

$$\tilde{\mathcal{P}}(p) = \tilde{E}(p) + u$$

and

$$\hat{w}(\underline{p}) = \hat{R},$$

where $\hat{w} \equiv w\tau^i_jP_j^{-1}$ is the real wage in terms of utility, hence accounting for local amenities and prices.

Proof. Define the real wage, adjusted for amenities, as $\hat{w} \equiv w\tau_jP_j^{-1}$, where we have used that $\tau^i_j = \tau_j$. By assumption, $\hat{b} \equiv b^i_j\tau_jP_j^{-1}$ is constant across regions. Define $\hat{F}_j(\hat{w}) \equiv F_j(w\tau_jP_j^{-1})$. Since $\theta^i_j = 1$, $\delta^i_j = \delta$, $a^i_{jx}(s_x) = 1$, and $\chi = 0$, the employed workers' value function (4) simplifies to

$$r\hat{W}(\hat{w}) = \hat{w} + \sum_{x\in\mathbb{J}}\left(\bar{v}_x \max\left[\int \hat{W}(\hat{w}')\,d\hat{F}_x(\hat{w}') - \hat{W}(\hat{w}), 0\right]\right) + \delta\left[\hat{U} - \hat{W}(\hat{w})\right]$$

and the unemployed worker's value function can be written as

$$r\hat{U} = \hat{b} + \sum_{x\in\mathbb{J}}\left(\bar{v}_x \max\left[\int \hat{W}(\hat{w}')\,d\hat{F}_x(\hat{w}') - \hat{U}, 0\right]\right),$$

which no longer depend on the worker type i or the current region of the worker j. Given that $\sigma \to 0$, workers accept any offer as long as $\hat{W}(\hat{w}') \geq \hat{W}(\hat{w})$. Since $W(\hat{w})$ is increasing in $\hat{w}$, this inequality implies that workers accept any offer as long as $\hat{w}' \geq \hat{w}$.

Define $\hat{p} \equiv p\tau_jP_j^{-1}$. The firm's maximization problem (9) becomes

$$\hat{\pi}_j(\hat{p}) = \frac{P_j}{\tau_j}\max_{\hat{w}}\left(\hat{p} - \hat{w}\right)\hat{l}(\hat{w}) \tag{42}$$

for all j, where $\hat{l}\left(\hat{w}\right) \equiv l_j(w\tau_j P_j^{-1})$. From $a^i_{jx}(s_x) = 1$ and $\chi = 0$ it follows that

$$\hat{l}(\hat{w}) = \frac{\hat{\mathcal{P}}\left(\hat{w}\right)}{\hat{q}\left(\hat{w}\right)} \quad \text{if } \hat{w} \geq \hat{R}, \tag{43}$$

where $\hat{R} \equiv R^i_j \tau_j P_j^{-1}$ is constant across regions by assumption. Since $\delta^i_j = \delta$, we have

$$\hat{q}\left(\hat{w}\right) = \delta + \sum_{x \in \mathbb{J}} \bar{v}_x \left[1 - \hat{F}_x\left(\hat{w}\right)\right] \tag{44}$$

and

$$\hat{\mathcal{P}}(\hat{w}) = \sum_{x \in \mathbb{J}} \left[\hat{E}_x\left(\hat{w}\right) + u_x\right], \tag{45}$$

where $\hat{E}_x\left(\hat{w}\right) \equiv E_x(w\tau_j P_j^{-1})$.

The first-order condition of the wage posting problem is

$$\frac{\left(\hat{p} - \hat{w}\right)\left(\frac{\partial \hat{l}(\hat{w})}{\partial \hat{w}}\right)}{\left(\hat{l}\left(\hat{w}\right)\right)} \quad = \quad 1, \tag{46}$$

where

$$\frac{\partial \hat{l}\left(\hat{w}\right)}{\partial \hat{w}} \quad = \quad \frac{\frac{\partial \hat{\mathcal{P}}(\hat{w})}{\partial \hat{w}} \hat{q}\left(\hat{w}\right) - \frac{\partial \hat{q}(\hat{w})}{\partial \hat{w}} \hat{\mathcal{P}}\left(\hat{w}\right)}{\hat{q}\left(\hat{w}\right)^2}.$$

Plugging this latter expression into the first-order condition gives

$$\frac{\left(\hat{p} - \hat{w}\right)\left(\frac{\partial \hat{\mathcal{P}}(\hat{w})}{\partial \hat{w}} \hat{q}\left(\hat{w}\right) - \frac{\partial \hat{q}(\hat{w})}{\partial \hat{w}} \hat{\mathcal{P}}\left(\hat{w}\right)\right)}{\hat{\mathcal{P}}\left(\hat{w}\right)\hat{q}\left(\hat{w}\right)} = 1. \tag{47}$$

We next define the productivity distribution $\tilde{\Gamma}(\hat{p})$ over the $\hat{p}$ across all firms in all regions, with associated density $\tilde{\gamma}(\hat{p})$. The minimum of this productivity distribution is $\underline{\hat{p}} = \min_j \left\{\underline{\hat{p}}_j\right\}$, and the maximum $\bar{\hat{p}}$ is defined analogously. To attract any workers, the least productive firm must pay at least the reservation wage

$$\hat{w}(\underline{\hat{p}}) = \hat{R}. \tag{48}$$

From (42), firms with the same $\hat{p}$ post the same wage $\hat{w}$ and therefore attract the same number of workers. Moreover, from the usual complementarity between firm size and productivity, more productive firms post higher real wages $\hat{w}$. Define a job offer distribution across regions as a function of productivity

$$\tilde{F}(\hat{p}) = \frac{1}{\bar{\tilde{v}}} \int_{\underline{\hat{p}}}^{\hat{p}} \tilde{v}(z)\tilde{\gamma}(z)dz,$$

where

$$\bar{\tilde{v}} = \int_{\underline{\hat{p}}}^{\bar{\hat{p}}} \tilde{v}(z)\tilde{\gamma}(z)dz$$

and from the solution to problem (10) the mass of vacancies across regions, $\tilde{v}(\hat{p})$, is

$$\tilde{v}(\hat{p}) = \sum_j \left[\left(\xi_j'\right)^{-1} (\tilde{\pi}_j(\hat{p})) \right].$$

Define $\tilde{x}(\hat{p}) \equiv \hat{x}(\hat{w}(p))$ for any $\hat{x}$. We can then re-define (44) and (45) using these definitions to obtain

$$\tilde{q}(\hat{p}) = \delta + \bar{\tilde{v}} \left[1 - \tilde{F}(\hat{p})\right] \tag{49}$$

and

$$\tilde{\mathcal{P}}(\hat{p}) = \tilde{E}(\hat{p}) + u \equiv (1-u)\tilde{G}(\hat{p}) + u, \tag{50}$$

where $\tilde{E}(\hat{p}) \equiv \sum_{x\in\mathbb{J}} \tilde{E}_x(\hat{p})$ and $u \equiv \sum_{x\in\mathbb{J}} u_x$, and $\tilde{G}(\hat{p}) \equiv \tilde{E}(\hat{p})/(1-u)$ is the distribution of workers to firms.

Using

$$\frac{\partial \tilde{x}(\hat{p})}{\partial \hat{p}} = \frac{\partial \hat{x}(\hat{w})}{\partial \hat{w}} \frac{\partial \hat{w}(\hat{p})}{\partial \hat{p}}$$

we re-write the first-order condition (47) as

$$\frac{\partial \hat{w}(p)}{\partial \hat{p}} = \frac{(\hat{p} - \hat{w}(\hat{p}))\left(\frac{\partial \tilde{\mathcal{P}}(\hat{p})}{\partial \hat{p}}\tilde{q}(\hat{p}) - \frac{\partial \tilde{q}(\hat{p})}{\partial \hat{p}}\tilde{\mathcal{P}}(\hat{p})\right)}{\tilde{\mathcal{P}}(\hat{p})\,\tilde{q}(\hat{p})}. \tag{51}$$

By definition of a steady state, inflows and outflows from unemployment must exactly balance

$$\tilde{q}(\hat{p})\,\tilde{E}(\hat{p}) = \bar{\tilde{v}}\tilde{F}(\hat{p})u,$$

and hence

$$\tilde{E}(\hat{p}) = \frac{\bar{\tilde{v}}\tilde{F}(\hat{p})u}{\tilde{q}(\hat{p})}.$$

The mass of unemployed is given from (19) by

$$u = \frac{\delta}{\bar{\tilde{v}} + \delta}.$$

Substituting these expressions into (50) gives

$$\tilde{\mathcal{P}}(\hat{p}) = \frac{\delta}{\tilde{q}\,(\hat{p})}.$$

Plugging this expression for the acceptance probability and its derivative into (51), we obtain

$$\frac{\partial \hat{w}(\hat{p})}{\partial \hat{p}} = \frac{-2\,(\hat{p} - \hat{w}(\hat{p}))\,\frac{\partial \tilde{q}(\hat{p})}{\partial \hat{p}}}{\tilde{q}\,(\hat{p})}. \tag{52}$$

Together, equations (44), (45), (48), and (52) are the functions stated in the proposition, redefined on $\hat{p}$ instead of on p, and are the same as in the standard Burdett-Mortensen model. $\square$

Q Parameters and Empirical Moments

In this section, we describe in more detail how each calibrated parameter (Supplemental Appendix Q.1) and each one of the targeted moments (Supplemental Appendix Q.2) are computed.

Q.1 Calibrated Parameters

We first describe how we compute the calibrated parameters shown in Table 3.

(1) Worker Skills

We estimate the AKM model with comparative advantage term for the worker's home region (East or West Germany)

$$\log(w_{it}) = \alpha_i + \psi_{J(i,t)} + \beta \mathbb{I}^{(h_i \neq R(J(i,t)))} + BX_{it} + \epsilon_{it}, \tag{53}$$

and describe details on the identification in Appendix F. As is standard, we estimate the model on the largest connected set of workers in our data, since identification of workers and firm fixed effects requires firms to be connected through worker flows.[72] This sample includes approximately 97% of West and East workers in the LIAB.

The estimation yields a comparative advantage estimate of $\beta = 0.019$, indicating a small *negative* comparative advantage towards the home region. Thus, a typical East-born worker is paid, controlling for firm characteristics, almost 1% more if she works in the West.[73] One possible explanation for this finding could be selection, since the workers that move to the West could be those whose skills are particularly valuable there. Since the presence of the premium would require the remaining frictions to be larger to rationalize the lack of East-to-West mobility, we conservatively set the comparative advantage to zero in our estimation.

We obtain the absolute advantage of workers from the average worker fixed effects by performing the projection

[72] We use a slightly longer time period from 2004-2014 to increase the share of firms and workers that are within the connected set.

[73] We attribute half of the overall wage differential to comparative advantage of the East worker in the West and half to comparative advantage of the West worker in the East. As discussed, we cannot identify these separately.

$$\hat{\alpha}_i = \eta^h \mathbb{I}_i^h + CX_i + \varepsilon_i, \tag{54}$$

where $\hat{\alpha}_i$ is the estimated worker fixed effect, $\mathbb{I}_i^h$ are dummies for the workers' home location, and X_i are dummies for worker age groups, gender, and college. We let NW be the omitted category, and obtain the η^h for the remaining three regions. We take their exponent since the AKM was estimated in logs, and present the exponentiated estimates in Table 3. We find that conditional on age, gender, and schooling, West-born workers earn, within the same firm, around 9% higher wages. The differences between locations within the East and within the West are small.

(2) Number of Firms by Region

To compute the mass of firms in each location, M_j, we count in our cleaned BHP sample in each region the number of firm-year observations in the period 2009-2014. We then compute the share of firms in each region.

(3) Workers by Birth Region

We obtain the share of workers born in each location, $\bar{D}^i$, from the population residing in each region in January 1991 from the Growth Accounting of the States (Volkswirtschaftliche Gesamtrechnung der Länder, VGRdL). This is the earliest month for which detailed population counts are available by East German states from official statistics. We do not use the LIAB data since it is not a representative sample and since it only starts in 1993. Our assumption in using residence to infer birth regions is that there was not too much net movement from East to West Germany before 1991. As a check, we obtain population estimates for the German Democratic Republic (GDR) in 1981 from Franzmann (2007), and combine these with West German population counts from the VGRdL. The population shares are, in fact, quite similar (In 1981, NW: 0.389, SW: 0.404, NE: 0.102, SE: 0.105).

(4) Separation Rate

We assume that the separation rates δ_j^i depend only on the work location j and set them equal to the monthly probabilities, computed in the LIAB data, that workers separate into unemployment or permanent non-employment (i.e. either retired or dropping out of the labor force). Specifically, we compute in each month the share of employed workers that become unemployed or permanently move out of the sample. We do not include workers that are temporarily out of the sample between employment spells since such workers are included in our definition of job-to-job movers. Notice that workers move out of the sample if they are either self-employed, not employed, or employed in a public sector job. We drop 2014, the last year of our sample, to avoid misclassifying workers. We then take a simple average across months for each location.

(5) Price Level

We take the price indices for each state in 2007 from the BBSR and write them forward using the inflation rate of each state obtained from the Growth Accounting of the States (Volkswirtschaftliche Gesamtrechnung der Länder, VGRdL). We aggregate the price indices in each year to the location-level by taking a population-weighted average using the population weights from the VGRdL. We then take a simple average across the years 2009-2014 for each location, and normalize Northwest to 1.

(6) Payments to Fixed Factors

We interpret the fixed factor in the model as land and set $\alpha\,(1-\eta)$ equal to 5%, which is the estimate of the aggregate share of land in GDP for the United States, see Valentinyi and Herrendorf (2008). It is worthwhile to note that $\alpha\,(1-\eta)$ does not affect the estimation of the model since we feed in the local price levels directly. It is only relevant for the general equilibrium counterfactuals.

(7) Elasticity of the Matching Function

We assume that the matching function has constant returns to scale - as standard in the literature, see Petrongolo and Pissarides (2001) - and puts equal weight on applications and vacancies, which gives $\chi = 0.5$. The value of χ only affects the parameters of the vacancy costs and does not influence the other parameters in the estimation procedure, as it is not separately identified from $\xi_{0,j}$ and ξ_1.

(8) Interest Rate

Since individuals in our model are infinitely lived, the interest rate r accounts for both discounting and rates of retirement or death. We pick a monthly interest rate equal to 0.5%.

Q.2 Moments for Estimation

Next, we turn to the 305 empirical moments targeted in the estimation and described in Table 4. Unless otherwise mentioned, all moments are constructed using the cleaned data described in the data section of the main text, for the core sample period 2009-2014.

We follow the order of the table in describing each set of moments in detail.

Q.2.1 Wage Gains of Job-to-Job Movers

We compute the average wage gains of job-to-job movers between any combination of locations by estimating on all employed workers in our cleaned LIAB data the specification

$$\Delta \log(w_{it}) = \sum_{h \in \mathbb{H}} \sum_{s \in \mathbb{S}} \beta_{hs} d_{it}^{s} \mathbb{I}_i^h + BX_{it} + \gamma_t + \epsilon_{it}, \tag{55}$$

where $\Delta \log(w_{it})$ is the difference between a worker's log average real wage in the year after the job-to-job move and her log real wage in the job before the switch, d_{it}^s are dummies that are equal to one if worker i makes a job-to-job switch of type s at time t, and γ_t are year fixed effects. Here, $\mathbb{S}$ is the set of the 12 possible cross-location migration moves (NW-SW, NW-NE, NW-SE, SW-NW, and so on) and the 4 possible within-location moves. We define migration moves as all job switches across locations that entail the worker updating her residence county, plus all job moves that take the worker further away from her current residence as long as the worker's residence remains within 200km of her job, as discussed in more detail in Appendix B. We interact the move dummies with four indicator variables $\mathbb{I}_i^h$ for worker i's home location (NW, SW, NE, or SE) to identify average wage gains separately for different types of workers. Thus, in total we have 16*4=64 move-by-birth dummies of interest. The controls X_{it} contain dummies for eight age groups (26-30 years, 31-35 years, ... 56-60 years, older than 60 years, where the group of under 26 year olds is the omitted category), a dummy for whether the worker has a college degree, and a dummy for the worker's gender. The controls also include 12 dummies for non-migration cross-location job moves (for example because the worker did not change residence location and moved closer to her residence), interacted with birth location dummies. We include these latter controls so that the variables of interest, d_{it}^s, pick up wage gains of migrants relative to stayers, the omitted category. Table S18 shows the estimated coefficients on the migration dummies, and their standard errors. All coefficients are tightly estimated given the very large sample size. For each coefficient, the first column indicates the worker's home location, the second column shows the location of the worker's initial job, and the top row shows the location of the worker's new job.

Table S18: Average Log Wage Gains for Job-Job Movers by Birth and Migration Locations

Dep. var.: d_{it}^{s}	New Job Location:	NW		SW		NE		SE	
Home Location	Origin Job Location	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
NW	NW	0.109	(0.001)	0.282	(0.011)	0.136	(0.023)	0.244	(0.041)
	SW	0.195	(0.013)	0.090	(0.006)	0.048	(0.072)	0.108	(0.054)
	NE	0.127	(0.022)	0.206	(0.069)	0.051	(0.008)	0.075	(0.052)
	SE	0.164	(0.038)	0.219	(0.039)	0.202	(0.068)	0.072	(0.011)
SW	NW	0.100	(0.008)	0.169	(0.014)	0.120	(0.075)	0.134	(0.071)
	SW	0.281	(0.011)	0.107	(0.001)	0.280	(0.062)	0.186	(0.024)
	NE	0.260	(0.077)	0.138	(0.051)	0.049	(0.012)	0.029	(0.045)
	SE	0.152	(0.053)	0.161	(0.023)	0.130	(0.038)	0.085	(0.007)
NE	NW	0.081	(0.004)	0.150	(0.031)	0.031	(0.018)	0.101	(0.055)
	SW	0.177	(0.030)	0.082	(0.006)	-0.020	(0.026)	0.097	(0.043)
	NE	0.236	(0.012)	0.283	(0.027)	0.057	(0.002)	0.168	(0.015)
	SE	0.270	(0.060)	0.276	(0.038)	0.076	(0.025)	0.093	(0.008)
SE	NW	0.085	(0.008)	0.189	(0.033)	0.065	(0.056)	0.044	(0.026)
	SW	0.207	(0.032)	0.072	(0.006)	0.052	(0.077)	0.034	(0.017)
	NE	0.153	(0.060)	0.176	(0.056)	0.045	(0.010)	0.112	(0.027)
	SE	0.325	(0.024)	0.269	(0.013)	0.111	(0.014)	0.091	(0.002)

Notes: The table shows the average wage gains of job movers by origin location-destination location-home location.

Q.2.2 Flows of Job-to-Job Movers

We compute in our cleaned LIAB data in each month the number of workers making a job-to-job move between any combination of locations. There are 12 possible migration moves (NW-SW, NW-NE, NW-SE, SW-NW, and so on) and 4 possible within-location job moves. We define migration moves as all job switches across locations that entail the worker updating her residence county, plus all job moves that take the worker further away from her current residence as long as the worker's residence remains within 200km of her job, as discussed in more detail in Appendix B. We compute these movers by worker home location (i.e., their type). In total, there are thus 16*4=64 worker flows. We translate these raw flows into shares by dividing them in each month by the total number of employed workers of the given type in the location of the origin job. We exclude workers that leave the sample in the next month from this calculation, since we do not have information on whether they move or stay within the location. We also exclude the last month in our data, December 2014, for the same reason. We then take the average of these shares across months.

Table S19 shows the resulting shares. For each worker home location (first column) and location of the current job (second column), we show the share of workers changing jobs to a given destination location (indicated in the top row) in an average month, as a fraction of all employed workers of the given home location and current location.

Table S19: Job-to-Job Migration Flows Between Locations by Birth Location

Birth Location	Move to Location: Current Work Location	NW	SW	NE	SE
NW	NW	0.977%	0.020%	0.004%	0.002%
	SW	0.208%	1.094%	0.006%	0.009%
	NE	0.194%	0.030%	0.948%	0.028%
	SE	0.133%	0.068%	0.041%	1.057%
SW	NW	0.983%	0.215%	0.007%	0.007%
	SW	0.025%	1.244%	0.001%	0.006%
	NE	0.084%	0.133%	0.881%	0.074%
	SE	0.033%	0.159%	0.027%	1.111%
NE	NW	1.054%	0.032%	0.077%	0.011%
	SW	0.073%	1.247%	0.069%	0.029%
	NE	0.043%	0.010%	0.911%	0.031%
	SE	0.038%	0.047%	0.124%	1.006%
SE	NW	1.031%	0.089%	0.019%	0.094%
	SW	0.043%	1.179%	0.010%	0.117%
	NE	0.031%	0.030%	0.608%	0.138%
	SE	0.011%	0.033%	0.020%	1.080%

Notes: The table presents the share of employed workers that make a job-to-job move for each triplet of home location, current location, destination location in an average month.

Q.2.3 Employment Share

We count in our cleaned LIAB data in each month the number of employed workers of a given type (home location) living in each location, and we divide by the total number of employed workers of that type in our LIAB data to obtain shares. We then average across months. We similarly compute the share of employed workers working in each location. Table S20 presents these worker shares. The first column indicates the home location of the worker, and the second column indicates the residence/work location. Columns 3 and 4 show the shares of employed workers of the given home location that live in a given location (column 3) and work in a given location (column 4). In our baseline estimation, we use the residence location as target for the distribution of labor since it more closely reflects the way in which we define a cross-location move. We use the work location in some of the robustness checks in Supplementary Appendix T.

Table S20: Share of Employed Workers by Location of Residence or Work Location

Home Location	Location of...	...Residence	...Work
NW	NW	92.7%	92.0%
	SW	4.4%	5.6%
	NE	2.0%	1.6%
	SE	0.8%	0.8%
SW	NW	4.3%	6.1%
	SW	92.5%	90.9%
	NE	0.8%	0.8%
	SE	2.3%	2.2%
NE	NW	7.6%	12.8%
	SW	4.3%	5.8%
	NE	84.7%	77.1%
	SE	3.4%	4.4%
SE	NW	3.0%	4.4%
	SW	6.7%	9.8%
	NE	2.5%	3.9%
	SE	87.7%	81.9%

Notes: The table shows the fraction of employed workers of the home location indicated in column 1 that live in the location indicated in column 2 and that work the location indicated in column 2, respectively.

Q.2.4 Unemployment Share

We count in our cleaned LIAB data in each month the number of unemployed workers of a given type (home location) living in each location, and we divide by the total number of unemployed workers of that type to obtain shares. We then average across months. We similarly compute the share of unemployed workers by last work location of the worker. We obtain the last work location as the location of the most recent job before the unemployment spell, and we exclude unemployed workers whose last job was in Berlin and workers that do not have a prior employment spell. Table S21 presents these worker shares. In our baseline estimation, we use the residence location as target for the distribution of labor since it more closely reflects the way in which we define a cross-location move. We use the work location in some of the robustness checks in Supplementary Appendix T.

Table S21: Share of Unemployed Workers by Location of Residence or Location of Last Job

	Location of...	Residence	Last Job
Home Location			
NW	NW	90.9%	89.1%
	SW	4.5%	6.5%
	NE	3.3%	3.1%
	SE	1.3%	1.4%
SW	NW	4.7%	7.4%
	SW	90.2%	87.5%
	NE	1.5%	1.5%
	SE	3.6%	3.6%
NE	NW	4.9%	10.6%
	SW	2.9%	5.5%
	NE	89.5%	78.8%
	SE	2.7%	5.2%
SE	NW	2.4%	4.2%
	SW	4.8%	9.2%
	NE	2.9%	4.2%
	SE	90.0%	82.4%

Notes: The table shows the fraction of unemployed workers of the home location indicated in column 1 that live in the location indicated in column 2 and whose last job was in the location indicated in column 2, respectively.

Q.2.5 Average AKM Firm Fixed Effect by Worker Location and Worker Type

We perform in our cleaned LIAB data a regression of the firm fixed effects from our AKM model on dummies for an employed worker's residence location, by worker type, and controls

$$fe_{it} = \sum_{h \in \mathbb{H}} \sum_{l \in \mathbb{L}} \beta_{hl} \mathbb{I}_{it}^{l} \mathbb{I}_{i}^{h} + BX_{it} + \epsilon_{it}, \tag{56}$$

where fe_{it} is the firm fixed effect of the firm at which worker i is employed at time t, obtained from the AKM estimated in Supplemental Appendix Q.1, $\mathbb{I}_{it}^{l}$ are dummies that are equal to one if worker i lives in location l at time t, $\mathbb{L} = \{NW, SW, NE, SE\}$, and $\mathbb{I}_{i}^{h}$ are dummies that are equal to one if worker i's home location is location h. Here, $\mathbb{H}$ is the set of the 4 possible birth locations (NW, SW, NE, and SE). The controls X_{it} contain dummies for eight age groups (26-30 years, 31-35 years, ... 56-60 years, older than 60 years, where the group of under 26 year olds is the omitted category), a dummy for whether the worker has a college degree, and a dummy for the worker's gender. In a second specification, we run an analogous regression using dummies for a worker's work location rather than her residence location.

Table S22 shows the estimated coefficients. The first two columns with data show the estimated coefficients β_{hl} for workers with home location h indicated in column 1 and residence location l indicated in column 2, together with their standard errors. Each of the coefficients is relative to the coefficient of workers born in the Northwest and living in the Northwest. The last two data columns show the analogous estimates for workers with home location h indicated in column 1 and work location l indicated in column 2. In our baseline estimation, we use the moments related to the residence location as target since they more closely reflect the way in which we define a cross-location move. We use the moments related to the work location in some of the robustness checks in Supplementary Appendix T.

Table S22: Firm Fixed Effects by the Birth and Current Location of Workers

Dep. var.: fe_{it}	Location of...	Live		Work	
Home Location		Coefficient	SE	Coefficient	SE
NW	SW	-0.064	0.001	-0.060	0.001
	NE	-0.141	0.001	-0.210	0.001
	SE	-0.139	0.002	-0.147	0.002
SW	NW	-0.036	0.001	-0.038	0.001
	SW	-0.046	0.000	-0.046	0.000
	NE	-0.193	0.002	-0.213	0.002
	SE	-0.165	0.001	-0.187	0.001
NE	NW	-0.090	0.001	-0.070	0.001
	SW	-0.104	0.001	-0.113	0.001
	NE	-0.198	0.000	-0.211	0.000
	SE	-0.119	0.001	-0.163	0.001
SE	NW	-0.056	0.001	-0.062	0.001
	SW	-0.090	0.001	-0.088	0.001
	NE	-0.171	0.002	-0.163	0.001
	SE	-0.169	0.000	-0.177	0.000

Notes: The table shows the estimated coefficients β_{hl} in specification (56). The first two columns with data show the coefficients for workers with home location h indicated in column 1 and residence location l indicated in column 2, together with their standard errors. Each of the coefficients is relative to the coefficient of workers born in the Northwest and living in the Northwest. The last two data columns show the analogous estimates for workers with home location h indicated in column 1 and work location l indicated in column 2.

Q.2.6 AKM Firm Fixed Effect by Firm Location

We collapse the cleaned LIAB data to the firm-level and perform a regression of the firm fixed effects from our AKM model on dummies for each firm's location:

$$fe_j = \sum_{l \in \mathbb{L}} \beta_l \mathbb{I}_j^l + \epsilon_j, \tag{57}$$

where fe_j is the estimated firm fixed effect of firm j, and $\mathbb{I}_j^l$ are dummies that are equal to one if firm j is in location l. Using the firm fixed effects instead of actual real wages isolates the firm component of wages and removes differences in wages due to worker composition. We do not include industry controls since we want our model to be consistent with the aggregate wage gaps between locations, which could partially be due to differences in industry composition. Our estimated productivity shifters therefore also reflect industry differences across locations, although they are not quantitatively important, as shown in Supplemental Appendix L. For similar reasons, we do not include demographic controls. Table S23 presents the estimated coefficients β_l for firm location l indicated in column 1, where NW is the omitted category.

While in our baseline specification we do not include controls since we simply want to capture the differences in average firm productivity across locations, we also computed an alternative specification with a vector of controls X_j. We control for firm-level averages, averaged across all workers at the firm, of dummies for eight age groups (26-30 years, 31-35 years, ... 56-60 years, older than 60 years, where the group of under 26 year olds is the omitted category), a dummy for whether a worker has a college degree, and a dummy for workers' gender. The results barely change.[74]

Table S23: Firm Fixed Effect by Location

Dep. var.: fe_j	Coef on Firm FE	SE
Location		
SW	.001	.002
NE	-.166	.002
SE	-.141	.003

Notes: The table presents the estimated coefficients β_l from specification (57) for firm location l indicated in column 1, where NW is the omitted category.

[74]Specifically, the three coefficients for SW, NE, and SE become: -0.001, -0.154, -.144.

Q.2.7 GDP per Capita

We obtain nominal GDP per capita for each federal state from the National Accounts of the States (Volkswirtschaftliche Gesamtrechnungen der Länder, VGRdL) for each year. To translate the nominal figures into real ones, we compute the price level in each state in 2007 as a population-weighted average across the county-level prices reported by the BBSR. We then extend the resulting state-level prices in 2007 forward to 2014 using the state-level deflators available in the VGRdL. We deflate each state's nominal GDPpc with the resulting prices in each year to obtain state-level real GDPpc in each year, and we aggregate to the location level using each state's population in each year, also reported in the VGRdL. We take a simple average over the years in our core sample period and normalize real GDP per capita in NW to 1. Table S24 presents the results.

Table S24: Average GDP per capita by Location

Location	Avg. GDP pc	Normalized to 1
NW	35,119	1
SW	38,391	1.09
NE	25,756	0.73
SE	27,016	0.77

Notes: The table shows a simple average over the GDPpc of each location in the period 2009-2014. We obtain nominal GDPpc from the National Accounts of the States (Volkswirtschaftliche Gesamtrechnungen der Länder, VGRdL), and construct price deflators from the inflation rates in the VGRdL and the price data from the survey of the Federal Institute for Building, Urban Affairs and Spatial Development (BBSR).

Q.2.8 Unemployment Rate

We obtain the unemployment rate (Arbeitslosenquote bezogen auf abhängige, zivile Erwerbspersonen) of each federal state in each month from the official unemployment statistics of the German Federal Employment Agency. We compute this moment from the official statistics rather than from the smaller LIAB sample since the latter is not representative and includes unemployed individuals only for as long as they are receiving unemployment benefits. We aggregate across states to locations using each state's labor force as weight, and take a simple average across the months in our core sample period. Table S25 shows the estimates.

Table S25: Unemployment Rate by Location

Location	Unemployment Rate
NW	8.82%
SW	5.35%
NE	12.58%
SE	11.16%

Note: The table shows the average unemployment rate in each location in the period 2009-2014, computed from the official unemployment statistics of the German Federal Employment Agency.

Q.2.9 Deciles of Firm Size Distribution

We obtain in our cleaned BHP data the number of full-time workers employed at each firm in each year in our core sample period. We then remove variation due to observables that are not present in our model by performing, for each work location, the following regression

$$\ln(y_{jlt}^{size}) = B_l X_{jlt} + \gamma_t + \epsilon_{jlt}, \tag{58}$$

where y_{jlt}^{size} is the number of full-time workers of firm j in location l in year t and γ_t are year fixed effects. The controls X_{jlt} include the share of male full-time workers, the share of young full-time workers (of age less than 30 years old), and the share of full-time workers of medium age (30-49 years old). The controls also include the share of full-time workers of low qualifications (individuals with a lower secondary, intermediate secondary, or upper secondary school leaving certificate but no vocational qualifications) and the share of full-time workers of medium qualifications (individuals with a lower secondary, intermediate secondary, or upper secondary school leaving certificate and a vocational qualification). Finally, we include 3-digit time-consistent industry dummies based on Eberle et al. (2011) (WZ93 classification).

Based on the four regressions (one for each work location l) we obtain residuals for the log number of workers at each firm j, $\hat{\epsilon}_{jlt}^{size}$. We add back the mean log number of workers in each location, $\overline{\ln(y_{jlt}^{size})}$, to obtain a cleaned number of workers, $\hat{y}_{jlt}^{size} = \exp[\overline{\ln(y_{jlt}^{size})} + \hat{\epsilon}_{jlt}^{size}]$. We then construct deciles of the distribution of residualized firm size in each location and compute the share of residualized workers employed in each decile. Table S26 presents the resulting shares. Each column of the table shows the share of the location's workers employed at firms in the decile of the location's residualized firm size distribution indicated in column 1.

Table S26: Share of Workers by Firm Size Decile and Location

Firm Size Decile	NW	SW	NE	SE
1	0.009	0.008	0.010	0.009
2	0.013	0.013	0.015	0.015
3	0.017	0.016	0.019	0.019
4	0.022	0.021	0.024	0.024
5	0.029	0.028	0.034	0.033
6	0.038	0.036	0.043	0.042
7	0.052	0.050	0.058	0.057
8	0.074	0.071	0.083	0.081
9	0.124	0.119	0.136	0.135
10	0.622	0.636	0.578	0.584

Notes: Each column of the table shows the share of the location's workers employed at firms in the decile of the location's firm size distribution indicated in column 1. The number of workers used in the table is residualized using firms' share of male workers, share of workers with low and medium skills, share of young and medium-aged workers, and industry dummies, as described in the text.

Q.2.10 Slope of Firm Wage vs Firm Size Relationship

We obtain in our cleaned BHP data the number of full-time workers and their average wage at each firm, where top coded wages are imputed as in Card et al. (2013). We then remove variation due to observables that is not present in our model by performing, for each work location l, the following regression

$$\ln(y_{jlt}) = B_l X_{jlt} + \gamma_t + \epsilon_{jlt},$$

where y_{jlt} is either the number of full-time workers of firm j in location l in year t or their average wage, and γ_t are year fixed effects. The controls X_{jlt} include the share of male full-time workers, the share of young full-time workers (of age less than 30 years old), and the share of full-time workers of medium age (30-49 years old). The controls also include the share of full-time workers of low qualification (individuals with a lower secondary, intermediate secondary, or upper secondary school leaving certificate but no vocational qualifications) and the share of full-time workers of medium qualification (individuals with a lower secondary, intermediate secondary, or upper secondary school leaving certificate and a vocational qualification). Finally, we include 3-digit time-consistent industry dummies based on Eberle et al. (2011) (WZ93 classification).

We obtain from these four regressions (one for each location l) residuals for the log real wage, $\hat{\epsilon}_{jlt}^{wage}$, and for the log number of workers, $\hat{\epsilon}_{jlt}^{size}$. We add back the mean of each variable in each location, $\overline{\ln(y_{jlt}^{wage})}$ and $\overline{\ln(y_{jlt}^{size})}$, to obtain a cleaned log real wage, $\ln(\hat{y}_{jlt}^{wage}) = \overline{\ln(y_{jlt}^{wage})} + \hat{\epsilon}_{jlt}^{wage}$ and a cleaned log number of workers, $\ln(\hat{y}_{jlt}^{size}) = \overline{\ln(y_{jlt}^{size})} + \hat{\epsilon}_{jlt}^{size}$ for each firm. We then regress the residualized log real wage on the residualized log number of workers in each location

$$\ln(\hat{y}_{jlt}^{wage}) = \beta_{0,l} + \beta_{1,l} \ln(\hat{y}_{jlt}^{size}) + \varepsilon_{jlt}, \tag{59}$$

and report the slope coefficients $\beta_{1,l}$ in Table S27. We also plot the non-parametric relationships between $\ln(\hat{y}_{jlt}^{wage})$ and $\ln(\hat{y}_{jlt}^{size})$ in Figure A11, panel (a).

Table S27: Log Wage on Log Firm Size by Location

Dep. var.: $\ln(\hat{y}_{jlt}^{wage})$	Coefficient	SE
Location		
NW	.124	.000
SW	.124	.000
NE	.110	.001
SE	.109	.001

Notes: The table presents the coefficients $\beta_{1,l}$ of regression (59), by location of the firm, indicated in the first column. The residualization procedure is described in the text.

Q.2.11 Slope of Wage Gains of Job-to-Job Movers by Origin Firm Wage

We identify in our cleaned LIAB data all job-to-job moves and determine for each move the origin location of the worker (NW, SW, NE, or SE). We restrict the dataset to only these observations. We compute the log real wage gain associated with each job-to-job move, defined as the difference between a worker's log average real wage in the year after the job-to-job move and her log real wage in the job before the switch. We then residualize these wage gains to take out observable heterogeneity not present in our model by running, separately for each location l of the initial job, the regression

$$\Delta \ln(w_{ilt}) = B_l X_{ilt} + \gamma_t + \epsilon_{ilt}, \tag{60}$$

where $\Delta \ln(w_{ilt})$ is the log real wage gain associated with the move and γ_t are year fixed effects. The controls X_{ilt} contain dummies for eight age groups (26-30 years, 31-35 years, ... 56-60 years, older than 60 years, where the group of under 26 year olds is the omitted category), a dummy for whether the worker has a college degree, a dummy for the worker's gender, and 3-digit time-consistent industry (of the origin firm) dummies based on Eberle et al. (2011) (WZ93 classification). From these four regressions (one for each location l), we construct residuals for the log real wage gain, $\hat{\epsilon}^{gain}_{ilt}$. We add back the mean of the log real wage gain in each location, $\overline{\Delta \ln(w_{ilt})}$, to obtain a cleaned log real wage, $\Delta \ln(\hat{w}_{ilt}) = \overline{\Delta \ln(w_{ilt})} + \hat{\epsilon}^{gain}_{ilt}$. We similarly residualize the log real wage of the worker at the origin firm, $\ln(w_{ilt-1})$, to obtain the residualized initial log real wage, $\ln(\hat{w}_{ilt-1})$. We then regress the residualized log real wage gains on the residualized log initial real wages in each location

$$\Delta \ln(\hat{w}_{ilt}) = \beta_{0,l} + \beta_{1,l} \ln(\hat{w}_{ilt-1}) + \varepsilon_{ilt} \tag{61}$$

and report the slope coefficients $\beta_{1,l}$ in Table S28. In this table, each row shows the estimated regression coefficient on the residualized log initial wage for job-to-job moves originating in the location indicated in the first column. We also plot the non-parametric relationships between $\Delta \ln(\hat{w}_{ilt})$ and $\ln(\hat{w}_{ilt-1})$ in Figure A11, panel (b).

Table S28: Log Wage Gain of Movers by Initial Wage

Dep. var.: $\Delta \ln(\hat{w}_{irt})$	Coefficient	SE
Location		
NW	-.549	.001
SW	-.577	.000
NE	-.562	.003
SE	-.561	.002

Note: The table presents the coefficients $\beta_{1,l}$ of regression (61), by location of the origin firm. The residualization procedure is described in the text.

Q.2.12 Slope of Separation/Quit Rate by Initial Wage

We identify in our cleaned LIAB data in each month the workers moving job-to-job, from a job into unemployment, or from a job to permanently out of the sample. We construct a dummy that is equal to one if worker i with current job in location l at time t makes such a move, d^{sep}_{ilt}. We also obtain the log real wage of each worker in the job prior to the move, $\ln(w_{ilt})$. We then residualize these two variables to take out observable heterogeneity not present in our model by running, separately for each location of the initial job, the regression

$$y_{ilt} = B_l X_{ilt} + \gamma_t + \epsilon_{ilt}, \tag{62}$$

where y_{ilt} is either the dummy indicating a separation or the worker's log real wage in the job prior to the move. The controls X_{ilt} contain dummies for eight age groups (26-30 years, 31-35 years, ... 56-60 years, older than 60 years, where the group of under 26 year olds is the omitted category), a dummy for whether the worker has a college degree, a dummy for the worker's gender, and 3-digit time-consistent industry (of the origin firm) dummies based on Eberle et al. (2011) (WZ93 classification). From these four regressions (one for each location l), we construct residuals for the log initial real wage, $\hat{\epsilon}^{wage}_{ilt}$, and for the separation dummy, $\hat{\epsilon}^{sep}_{ilt}$, and add back the mean of each variable in each location, $\overline{\ln(w_{ilt})}$ and $\overline{d^{sep}_{ilt}}$, to obtain a cleaned log wage, $\ln(\hat{w}_{ilt}) = \overline{\ln(w_{ilt})} + \hat{\epsilon}^{wage}_{ilt}$ and a cleaned separation dummy $\hat{d}^{sep}_{ilt} = \overline{\ln(d^{sep}_{ilt})} + \hat{\epsilon}^{sep}_{ilt}$. We then regress the residualized separation dummy on the residualized log wages for each location

$$\hat{d}^{sep}_{ilt} = \beta_{0,l} + \beta_{1,l} \ln(\hat{w}_{ilt}) + \varepsilon_{ilt} \tag{63}$$

and report the slope coefficients $\beta_{1,l}$ in Table S29. In this table, each row shows the estimated regression coefficient on the residualized log initial real wage for separations from jobs in the location indicated in the first column. We also plot the non-parametric relationships between $\hat{d}^{sep}_{ilt}$ and $\ln(\hat{w}_{ilt})$ in Figure A11, panel (c).

Table S29: Avg. Separation Rates of Workers by Initial Wage

Dep. var.: $\hat{d}^{sep}_{irt}$	Coefficient	SE
Location		
NW	-.029	.000
SW	-.033	.000
NE	-.037	.000
SE	-.036	.000

Notes: The table presents the coefficients $\beta_{1,l}$ of regression (63), by location of the firm. The residualization procedure is described in the text.

Q.2.13 Standard Deviation of Wage Gains of Movers

We identify in our cleaned LIAB data all migration moves between any combination of locations (NW-SW, NW-NE, NW-SE, SW-NW, and so on). We define migration moves as all job switches across locations that entail the worker updating her residence county, plus all job moves that take the worker further away from her current residence as long as the worker's residence remains within 200km of her job, as discussed in more detail in Appendix B. We also identify job-to-job moves within-location, for each of the four locations. We indicate for each move the home location of the worker making the move. We restrict the dataset to these job-to-job moves and compute the log real wage gain associated with each move, defined as the difference between a worker's log average real wage in the year after the job-to-job move and her log real wage in the job before the switch. We then residualize these wage gains to take out observable heterogeneity not present in our model by running, separately for each location of the initial job, the regression

$$\Delta \ln(w_{ilt}) = B_l X_{ilt} + \gamma_t + \epsilon_{ilt}, \tag{64}$$

where $\Delta \ln(w_{ilt})$ is the log real wage gain associated with the move of worker i with initial job in location l at time t. The controls X_{ilt} contain dummies for eight age groups (26-30 years, 31-35 years, ... 56-60 years, older than 60 years, where the group of under 26 year olds is the omitted category), a dummy for whether the worker has a college degree, and a dummy for the worker's gender. From these four regressions (one for each location of the initial job l), we construct residuals for the log real wage gain, $\hat{\epsilon}_{ilt}^{gain}$. We then compute the standard deviation of these residualized wage gains for each home location-origin-destination combination. These coefficients are in Table S30. For each worker home location (first column) and location of the current job (second column), we show the standard deviation of wage gains for workers changing jobs to a given destination location (indicated in the top row).

Table S30: Standard Deviation of the Residual Wage Gains for Job Movers

Home Location	New Job Location: / Current Job Location	NW	SW	NE	SE
NW	NW	0.564	0.763	0.640	0.772
	SW	0.656	0.546	0.655	0.546
	NE	0.545	0.671	0.442	0.486
	SE	0.562	0.435	0.589	0.435
SW	NW	0.558	0.660	0.652	0.644
	SW	0.743	0.543	0.948	0.734
	NE	0.834	0.682	0.413	0.463
	SE	0.625	0.589	0.392	0.437
NE	NW	0.445	0.587	0.522	0.584
	SW	0.573	0.457	0.473	0.520
	NE	0.651	0.752	0.455	0.684
	SE	0.695	0.503	0.525	0.472
SE	NW	0.477	0.613	0.485	0.499
	SW	0.661	0.470	0.691	0.530
	NE	0.640	0.628	0.424	0.578
	SE	0.729	0.645	0.526	0.471

Notes: The table shows the standard deviation of the residualized wage gains of job-to-job movers, $\hat{\epsilon}_{ilt}^{gain}$, for workers of a given home location (column 1) and current job location (column 2) that move jobs to a given destination location (top row). The residualization procedure is described in the text.

Q.2.14 Profit to Labor Cost Ratio

We obtain the pre-tax profits of all firms in Germany from the ORBIS database provided by the company Bureau van Dijk. We allocate firms to our four locations based on the ZIP code of their address, and drop firms with fewer than 5 employees since their profits are very noisy. We then construct the ratio of profits to labor costs by dividing pre-tax profits by total labor costs reported in ORBIS, and average across firms and years to compute the average ratio in each location. We drop outlier profit ratios below the 5th and above the 95th percentile of the distribution of profit ratios in each location, and compute the average over the remaining ratios. Table S31 presents the estimates.

Table S31: Average Ratio of Firm Profits to Labor Costs by Location

Location	Avg. Profit Share
NW	27.44%
SW	25.87%
NE	29.87%
SE	26.26%

Source: ORBIS database. Notes: The table presents the average ratio of pre-tax profits to total labor costs for firms in the location indicated in the first column.

R Identification of Moving Costs, Preferences, and Search Efficiency

In this section, we provide further details on how various spatial frictions are identified.

Moving Costs and Location Preferences: τ and κ. We can pin down these moments using the average wage gain conditional on a move for an individual of type i, employed in location j, and taking a job in location x[75]

$$\underbrace{\mathbb{E}\left[\log(w_x^i\theta_x^i) - \log(w_j^i\theta_j^i)\right]}_{\text{Average Observed Wage Gain}} = \underbrace{\log\left(\theta_x^i\right) - \log\left(\theta_j^i\right)}_{\text{Comparative Advantage}} + \tag{65}$$

$$\int\left(\int \underbrace{(\log w' - \log w)}_{\text{Wage Gain}} \underbrace{\frac{\mu_{jx}^{E,i}(w,w')}{\bar{\mu}_{jx}^{E,i}(w)}}_{\text{Rel. Prob. Accept}} \underbrace{\mathrm{d}F_x(w')}_{\text{Offers CDF}}\right) \underbrace{\frac{a_{jx}^{E,i}(w)}{\bar{a}_{jx}^{E,i}}\mathrm{d}E_j^i(w)}_{\text{Weighted Employment CDF}},$$

where $\bar{a}_{jx}^{E,i} \equiv \int a_{jx}^{E,i}(w)\,\mathrm{d}E_j^i(w)$ and $\bar{\mu}_{jx}^{i,E}(w) \equiv \int \mu_{jx}^{i,E}(w,w')\,\mathrm{d}F_x(w')$.

Given offer distributions $F_x(\cdot)$, employment distributions $E_j^i(w)$, and the share of applications coming from each firm $\frac{a_{jx}^{E,i}(w)}{\bar{a}_{jx}^{E,i}}$, which are all mostly shaped by labor market frictions and therefore identified from within-location moments, as well as an estimate of skills θ_j^i, the equation directly relates the moving costs κ and local preferences τ to the relative wage gains of cross-location movers. Consider the limiting case when $\sigma \to 0$. In that case, workers accept an offer if and only if $W_x^i(w') - \kappa_{jx}^i \geq W_j^i(w)$. Since the value functions are increasing, the cutoff wage level $\hat{w}_{jx}^i(w)$ at which an individual of type i employed in location j would accept an offer from location x is an increasing function of w. An increase in κ_{jx}^i, or a decrease in τ_x^i, would raise this cutoff wage for any level of w. As the worker accepts only relatively better offers, the expected wage gain of a move increases in κ_{jx}^i and decreases in τ_x^i. As discussed in the main text, we separately identify moving costs and preferences by assuming that moving costs are identical for all worker types. Under that assumption, the location preferences are identified from the differences in wage gains for individuals of different types that make the same migration move.

[75] The flow utility of an individual i employed at a firm that pays wage w per efficiency unit in location j is given by $\frac{1}{P_j}\tau_j^i\theta_j^i w$. However, the observed nominal wage is simply $\theta_j^i w$, since τ_j^i does not enter into the wage.

Search Efficiency: z**.** Given an estimate of the labor market frictions, as well as estimates of skills, moving costs, and preferences (θ, κ, τ), we can recover the relative search efficiencies from the relative job-to-job flows within and between locations. The rate at which workers of type i currently employed in location j move towards a job in location x is given by

$$\underbrace{\psi_{jx}^{i}}_{\text{Quit Rate}} = \left[\underbrace{\vartheta_{x}^{1-\chi}}_{\text{Tightness}} \underbrace{\bar{a}_{jx}^{E,i}}_{\text{Applications}}\right] \tag{66}$$

$$\times\left[\int\left(\int \underbrace{\mu_{jx}^{E,i}\left(w,w'\right)}_{\text{Prob. Accept}} \underbrace{\mathrm{d}F_{x}\left(w'\right)}_{\text{Offer CDF}}\right) \underbrace{\frac{a_{jx}^{E,i}\left(w\right)}{\bar{a}_{jx}^{E,i}}\mathrm{d}E_{j}^{i}\left(w\right)}_{\text{Weighted Employment CDF}}\right]. \tag{67}$$

Since $\bar{a}_{jx}^{E,i} = z_{jx}^{i}\bar{s}_{x}^{E,i}$, where $\bar{s}_{x}^{E,i} \equiv \int s_{jx}^{E,i}\left(w\right)\mathrm{d}E_{j}^{i}\left(w\right)$, a lower search efficiency z_{jx}^{i} leads to lower job-to-job flows from location j to x given the acceptance probability $\mu_{jx}^{E,i}\left(w,w'\right)$, which is not directly affected by z_{jx}^{i} itself.

S Details on Computation and Estimation

S.1 Solution Algorithm

To solve the model, we follow a nested iterative procedure. Leveraging Proposition 1, we solve the model in the one-dimensional productivity space. In other words, rather than keep track of both wages and productivity, we simply solve for all the functions directly on the productivity support. Our procedure is as follows:

1. Make an initial guess for wage offer distributions, $\left\{w_{j}\left(p\right)\right\}_{j\in\mathbb{J}}$, firm vacancies $\left\{v_{j}\left(p\right)\right\}_{j\in\mathbb{J}}$, market tightness $\left\{\vartheta_{j}\right\}_{j\in\mathbb{J}}$, and vacancy sizes $\left\{\tilde{l}_{j}^{i}\left(p\right)\right\}_{j\in\mathbb{J},i\in\mathbb{I}}$, which gives

$$\left\{w_{j}\left(p;k\right),v_{j}\left(p;k\right),\vartheta_{j}\left(k\right),\tilde{l}_{j}^{i}\left(p;k\right)\right\}_{j\in\mathbb{J},i\in\mathbb{I},k=0},$$

   where k indexes the external iteration loop.

2. Given $\left\{w_{j}\left(p;k\right),v_{j}\left(p;k\right),\vartheta_{j}\left(k\right),\tilde{l}_{j}^{i}\left(p;k\right)\right\}_{j\in\mathbb{J},i\in\mathbb{I}}$, we solve the problem of the workers through value function iteration, which yields the value functions, and most importantly, the acceptance probabilities for every pair of firms (p,p') and worker type i,

and the job applications:

$$\left\{\tilde{\mu}_{jx}^{E,i}\left(p,p';k\right),\tilde{\mu}_{jx}^{U,i}\left(b,p';k\right)\right\}$$
$$\left\{\tilde{a}_{jx}^{E,i}\left(p;k\right),\tilde{a}_{jx}^{U,i}\left(b;k\right)\right\}_{j\in\mathbb{J},x\in\mathbb{J},i\in\mathbb{I}}.$$

3. Given $\left\{\tilde{\mu}_{jx}^{E,i}\left(p,p';k\right),\tilde{\mu}_{jx}^{U,i}\left(b,p';k\right),\tilde{a}_{jx}^{E,i}\left(p;k\right),\tilde{a}_{jx}^{U,i}\left(b;k\right)\right\}_{j\in\mathbb{J},x\in\mathbb{J},i\in\mathbb{I}}$, we use equation (16) to solve for $\left\{\tilde{q}_j^i\left(p;k\right)\right\}_{j\in\mathbb{J},i\in\mathbb{I}}$ and then iterate through equations (15), (17), and (18) until convergence to get a new guess for the firm size per vacancy $\left\{\tilde{l}_j^i\left(p;k+1\right)\right\}_{j\in\mathbb{J},i\in\mathbb{I}}$ that is consistent with the steady state employment distributions $\tilde{E}_j^i\left(p;k\right)$ and the probability of accepting offers $\tilde{\mathcal{P}}_j^i(p;k)$.

4. Finally, using $\left\{\tilde{l}_j^i\left(p;k\right),\tilde{q}_j^i\left(p;k\right)\right\}_{j\in\mathbb{J},x\in\mathbb{J},i\in\mathbb{I}}$, and solving for the boundary conditions at $w_j\left(\underline{p}_j\right)$ we can solve for a new guess for firm wages $\left\{w_j\left(p;k+1\right)\right\}_{j\in\mathbb{J}}$ using the system of differential equations in Proposition 1. Then, using the equations shown in the model section, we can get new guesses for vacancies and market tightness. We thus have a new vector

$$\left\{w_j\left(p;k+1\right),v_j\left(p;k+1\right),\vartheta_j\left(k+1\right),\tilde{l}_j^i\left(p;k+1\right)\right\}_{j\in\mathbb{J},i\in\mathbb{I}}$$

and can go back to point 2.

5. We iterate the external loop 2-4 until there is convergence within each iterative loop, namely the ones for value functions, vacancy sizes, and firm wages.

In order to compute the general equilibrium counterfactuals, we follow the same algorithm, but with two differences. First, as mentioned in the main text, during the estimation of the model, we solve - within each loop - for the unemployment benefits that yield a reservation wage equal to $R_j=\iota\underline{p}_j$. In the counterfactuals, instead, we keep the unemployment benefits fixed at their estimated value, and solve for the implied reservation wage. Second, while during the estimation we can keep each location's prices fixed at their observed values, in the counterfactual we must solve for the new equilibrium prices. Therefore, within each loop, we calculate each location's GDP and then we use it to calculate the new aggregate equilibrium prices.

S.2 Estimation Algorithm and Outcomes

The objective is to find a parameter vector ϕ^* that solves

$$\phi^* = \arg\min_{\phi \in \mathbb{F}} \mathcal{L}(\phi) \tag{68}$$

where

$$\mathcal{L}(\phi) \equiv \sum_x \left[\omega_x \left(T_x \left(m_x(\phi), \hat{m}_x \right) \right)^2 \right]$$

and $\mathbb{F}$ is the set of admissible parameter vectors, which is bounded to be strictly positive (or negative for search distance) and finite. In the choice of the function $T_x(\cdot)$, for most moments we follow Jarosch (2023) and Lise et al. (2016) and minimize the sum of the percentage deviations between model-generated and empirical moments; for others, instead, we use log differences. Specifically, for the moments that are already expressed in logs – rows (1), (2), (7), (8), (9), (12), (13) of Table 4 – $T_x(\cdot)$ is the percentage deviation: $T_x(m_x(\phi), \hat{m}_x) = \frac{m_x(\phi) - \hat{m}}{\hat{m}}$. For the other moments, $T_x(\cdot)$ is the log difference: $T_x(m_x(\phi), \hat{m}_x) = \log m_x(\phi) - \log \hat{m}$. Using the log difference is important especially for job flows to avoid giving excessive weight to deviations between model and data for flows that have very small magnitudes. Nonetheless, we have re-estimated the model using percentage deviations for all moments, and the results are broadly consistent, although the estimation procedure is less effective. We also introduce an additional weighting factor ω_x to give equal weight to each one of the 16 groups of parameters that we target, shown in Table 4.

The minimization algorithm that we use to solve the problem (68) combines the approaches of Jarosch (2023) and Lise et al. (2016), and Moser and Engbom (2022), both adapted to our needs.

We simulate, using Markov Chain Monte Carlo for classical estimators as introduced in Chernozhukov and Hong (2003), 200 strings of length 10,000 (+ 1,000 initial scratch periods used only to calculate posterior variances) starting from 200 different guesses for the vector of parameters ϕ_0. In the first run, we choose the initial guesses to span a large space of possible parameter vectors. In updating the parameter vector along the MCMC simulation, we pick the variance of the shocks to target an average rejection rate of 0.7, as suggested by Gelman et al. (2013). The average parameter values across the 200 strings for the last 1,000 iterations provide a first estimate of the vector of parameters. We then repeat the same MCMC procedure, but we start each string from the parameter estimates of the first step. We pick our final estimates as the average across the parameter vectors, picked from all strings, that are associated with the 100 smallest values of the likelihood functions.

Figure A4 in Appendix G illustrates our approach and how it slightly differs from Jarosch (2023) and Lise et al. (2016). The black dotted line shows the density function of the last 1,000 iterations across all strings. The usual approach is to pick the average across all these draws, which we highlight in the picture with a vertical black dotted line. However, this approach could be problematic if the parameter space is bounded, hence the estimated densities are not symmetric, as in our case for some parameters. Therefore, given our vector of parameters and likelihoods, we pick the optimal parameter following Moser and Engbom (2022), and simply select the vector of parameters that minimizes the objective function among all our draws.[76] Our estimates are shown with red dotted lines in the figure. For most parameters, they are almost identical to the alternative approach. Finally, the blue density functions shows the density, across all strings, of the 10 best outcomes within each string. This density provides a visual representation of the tightness of our estimates, which are, in general, quite good – especially for the key parameters that determine the spatial frictions. It is also relevant to notice that all the densities are single-peaked, which suggests that the model is, at least locally, tightly identified.

[76] More precisely, we take the average across the 100 best outcomes across all the 2,000,000 draws.

T Alternative Estimations

In this section, we compare the benchmark estimation to two alternatives to analyze how our structural estimates vary as a function of the way we define a cross-location move.

The first alternative includes as cross-location moves only those job switches across locations where the worker also updates her residence in the year of the move. Compared to the benchmark definition, we thus exclude job switches across locations where the worker does not update her residence but moves further away from her residence and stays within 200km of the county of residence. This narrow definition is based on the definition of cross-regional migration used in Section 3. The second alternative, instead, includes as cross-location moves any job-to-job switch across locations, regardless of residence. We refer to the first definition as "Only Migration Moves" and to the second one as "All Moves".

Of course, when we alter the definition of a cross-regional move, several of the targeted moments change. Table S32 lists all the moments and shows whether and how they change across estimations. All the moments directly related to cross-location moves – wage-gains (row 1), their standard deviations (row 13), and the frequency of flows (row 2) – change as we alter the definition of a cross-location move. In addition to that, we also need to change a few other targets for consistency. In particular, the moments that capture the distribution of labor across locations by birth-location must be reconsidered (rows 3, 4, and 5). In the benchmark estimation and in the "Only Migration Moves" one, we use the current residence location as target for the distribution of labor since it more closely reflects the way in which we define a cross-location move. In the "All Moves" estimation, instead, we use the work location for the distribution of labor since, in this case, we do not distinguish between living and work locations and we use only data on the latter. Thus, in Appendix Q.2.3, Q.2.4, and Q.2.5, we use the moments from the "Work" columns instead of from the "Live" columns.

For each one of the three estimations, we follow the same estimation method described in Appendix G. The model's fit is similar across all the estimations. In fact, Figures 5, A4, A8, and A9 for the benchmark estimation show a very similar fit to Figures S12, S14, S16, and S18, for the "Only Migration Moves" estimation, and to Figures S13, S15, S17, and S19 for the "All Moves" estimation. Likewise for Tables A8, S33, and S34, which show further details on the model's fit for the three estimations.

While the model fits are similar, the estimated parameters differ along a few dimensions, as expected, while still providing a similar qualitative perspective. Tables S35 and S36 report the estimated spatial frictions for the "Only Migration Moves" and the "All Moves" estimations. Under the "Only Migration Moves" definition, the frequency of cross-location flows observed in the data decreases and their average wage gains increase. As a result, the model estimates larger moving costs. They are approximately three times as large as the benchmark, but still much lower than estimates in the literature. The model also estimates slightly larger search frictions, although the difference is small. The reason for the latter outcome is that the sample restriction to only migration moves has a larger empirical effect on wage gains than on labor flows. As a result, the model estimates significantly higher moving costs, which, by themselves, reduce the flows almost by as much as in the data.

Including all moves has the opposite effect. The moving costs fall considerably, to approximately one third of the benchmark estimate. The search frictions are also affected (and reduced) but by a smaller extent. The biggest change is an increase in search home bias, which doubles the search efficiency of workers returning to their home region.

It is also worthwhile to notice that the home preference is slightly larger than in the benchmark in both alternative estimations. While this result may seem surprising at first, it actually encapsulates a key aspect of our estimation exercise. All the parameters are jointly estimated, and thus even if we target a lower asymmetry in the wage gains of cross-regional moves across worker types (as is the case for the "All Moves" estimation), the home preference does not have to decrease to match this fact. In fact, the estimation procedure pins down the home preference parameters mostly by comparing different types of job-to-job moves, and - in our data - the overall decrease in wage gains in the "All Moves" estimation relative to the benchmark is more dramatic that the decrease in the asymmetry. As a result, the home preference has to *increase* to match the data.

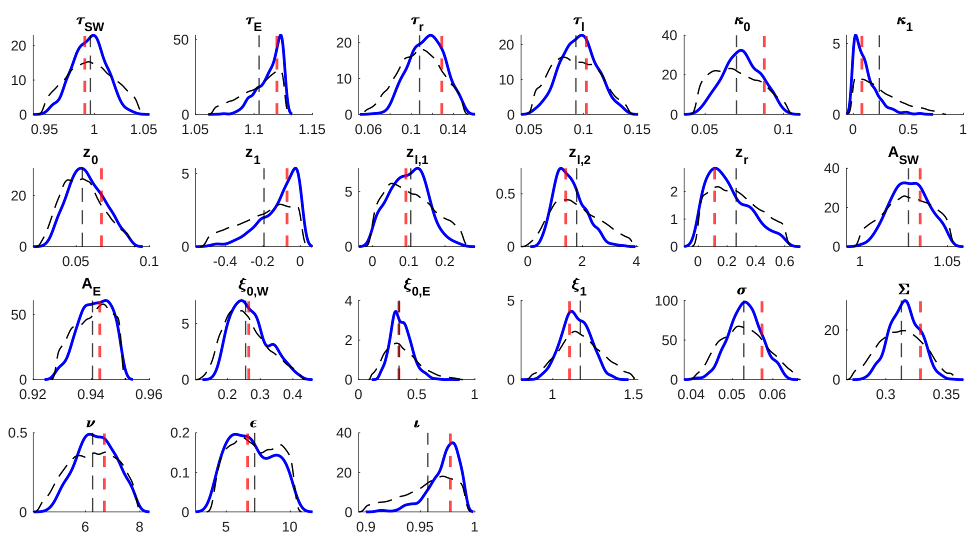
Finally, Tables S37 and S38 include all the primitive parameters and Figure S20 compares the outcomes of the three estimations and confirms that the biggest difference is for the moving costs.

Table S32: Moments used in the Estimation

	Moments	Benchmark	Migration Only	All Moves
(1)	Wage gains of job-job moves, by (i, j, x)	Benchmark	Migration	All
(2)	Frequency of job flows, by (i, j, x)	Benchmark	Migration	All
(3)	Employment shares, by (i, j)	Residence	Residence	Work
(4)	Unemployment shares, by (i, j)	Residence	Residence	Work
(5)	Firm component of wages, by (i, j)	Residence	Residence	Work
(6)	Average firm component of wages, by j	/	/	/
(7)	Relative GDP per worker, by j	/	/	/
(8)	Unemployment rates, by j	/	/	/
(9)	Deciles of firm-size distributions, by j	/	/	/
(10)	Slope of wage vs firm size relationship, by j	/	/	/
(11)	Slope of J2J wage gain vs firm wage, by j	/	/	/
(12)	Slope of separation rate vs firm wage, by j	/	/	/
(13)	Std of job-job wage gains, by (i, j, x)	Benchmark	Migration	All
(14)	Profit to labor cost ratio, by j	/	/	/

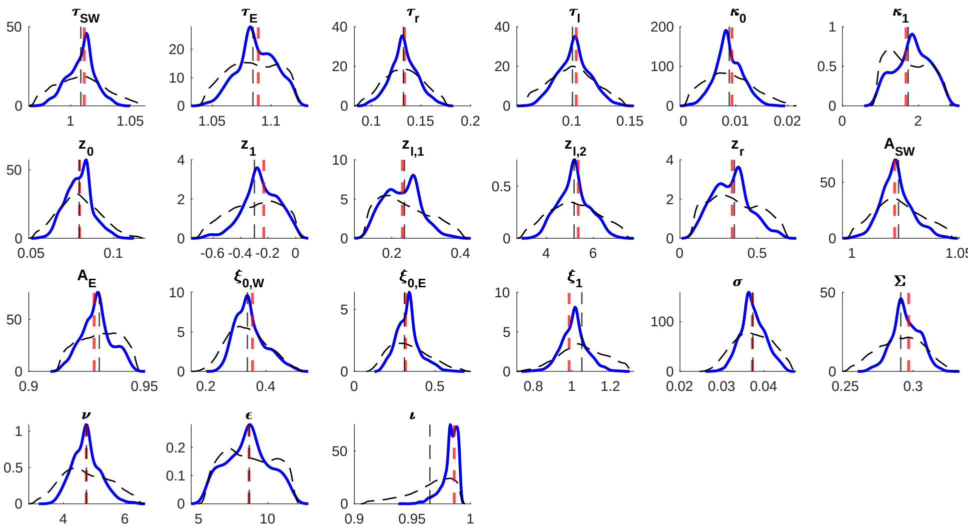
Notes: the table reports the moments used in the estimation and highlights whether they differ across the three estimations. If the moments used is identical across the three estimation, we include a slash symbol. Otherwise, we specify how the moments differ. Specifically, "Benchmark", "Migration", and "All" mean that these moments are computed using the corresponding definition of a cross-region job change. "Residence" and "Work" refer to whether we use the distribution of labor in Supplemental Appendices Q.2.3, Q.2.4, and Q.2.5 from the "Live" or from the "Work" column.

Figure S12: Estimation Outcome; Only Migration Moves



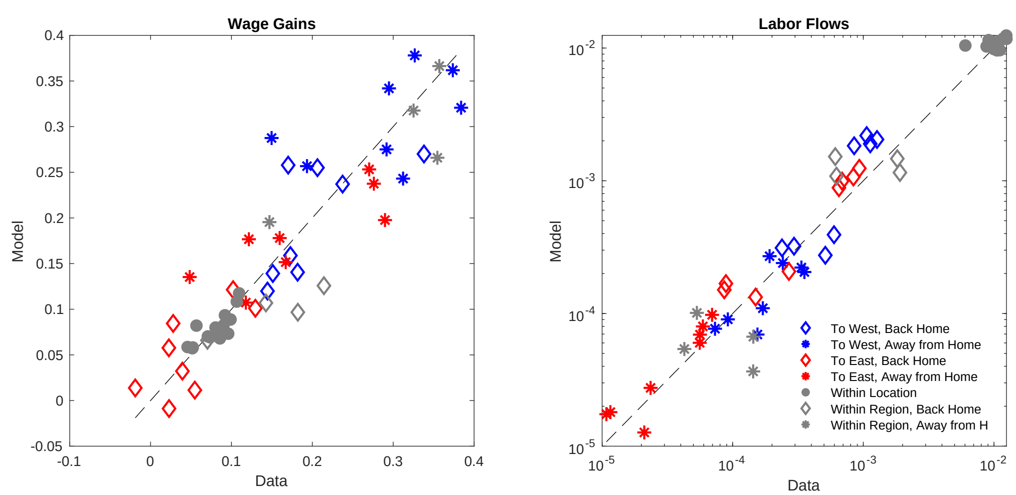
Notes: The figure shows the outcomes of the estimation for the "Only Migration Moves" estimation. Each panel shows a different one of the 21 estimated parameters. As described in the text, the black dashed and blue lines show the densities for different sub-sets of parameter draws. The red vertical lines are our estimated parameters, while the black vertical lines show the estimates that we would obtain with the alternative approach, described above. The top row shows the estimation results for τ_{SW}, τ_E, τ_r, τ_l, κ_0 and κ_1. The second row shows the results for z_0, z_1, $z_{l,1}$, $z_{l,2}$, z_r, and A_{SW}. The third row shows the estimates for A_E, $\xi_{0,W}$, $\xi_{0,E}$, ξ_1, σ, and Σ. The last row shows the estimates for ν, ϵ, and ι.

Figure S13: Estimation Outcome; All Moves



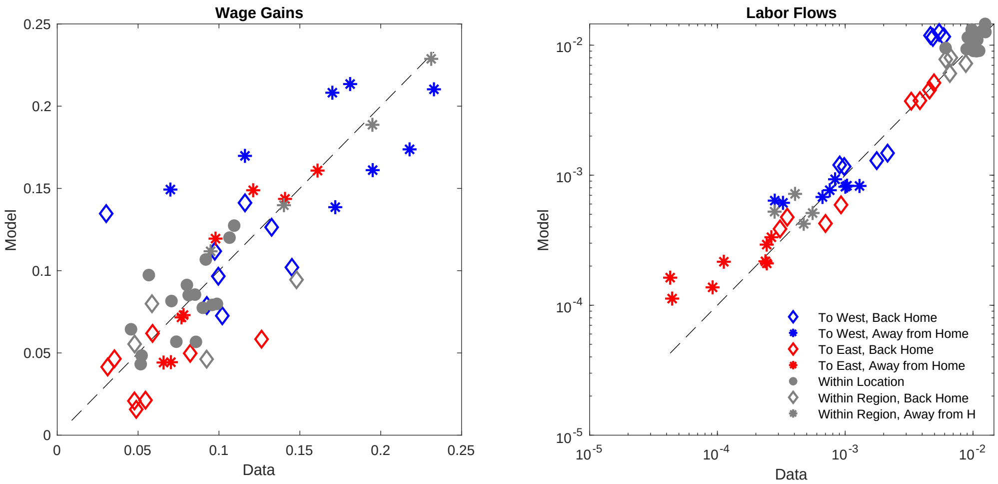
Notes: The figure shows the outcomes of the estimation for the “All Moves” estimation. Each panel shows a different one of the 21 estimated parameters. As described in the text, the black dashed and blue lines show the densities for different sub-sets of parameter draws. The red vertical lines are our estimated parameters, while the black vertical lines show the estimates that we would obtain with the alternative approach, described above. The top row shows the estimation results for τ_{SW}, τ_E, τ_r, τ_l, κ_0 and κ_1. The second row shows the results for z_0, z_1, $z_{l,1}$, $z_{l,2}$, z_r, and A_{SW}. The third row shows the estimates for A_E, $\xi_{0,W}$, $\xi_{0,E}$, ξ_1, σ, and Σ. The last row shows the estimates for ν, ϵ, and ι.

Figure S14: Wage Gains and Frequency of Job Flows; Only Migration Moves



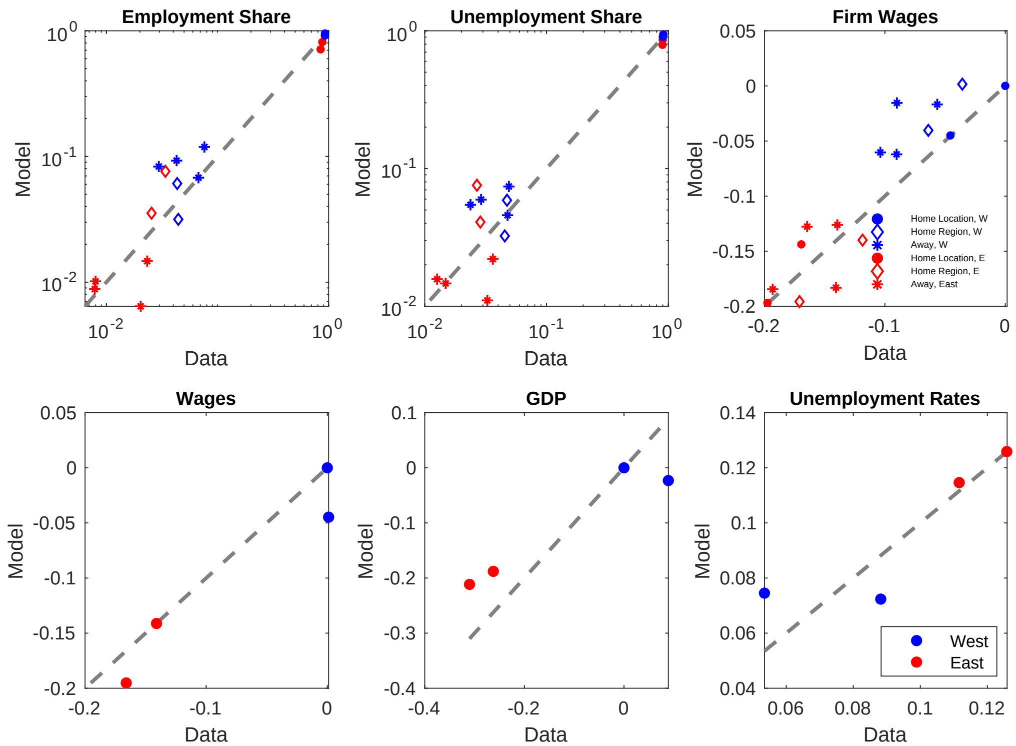
Notes: The left panel shows the average wage gains of different types of job-to-job moves in the data (x-axis) against the average wage gains in the model (y-axis) for the “Only Migration Moves” alternative. The right panel shows the frequency of each direction of the job-to-job move in the data (x-axis) against the frequency in the model (y-axis). Different types of moves are identified by a mix of colors and symbols, listed in the right panel. In total, there are 64 possible types of moves by (origin location, destination location, home location). The data moments used are listed in Supplemental Appendices Q.2.1 and Q.2.2. Gray symbols are moves within-region, blue symbols are moves to the West, and red symbols are moves to the East. Diamonds symbolize cross-location moves within-region back to the home location (in gray) or cross-region moves back to the home region (blue or red). Stars symbolize cross-location moves within-region away from the home location (in gray) or cross-region moves away from the home region (blue or red). Gray circles are moves within-location.

Figure S15: Wage Gains and Frequency of Job Flows: All Moves



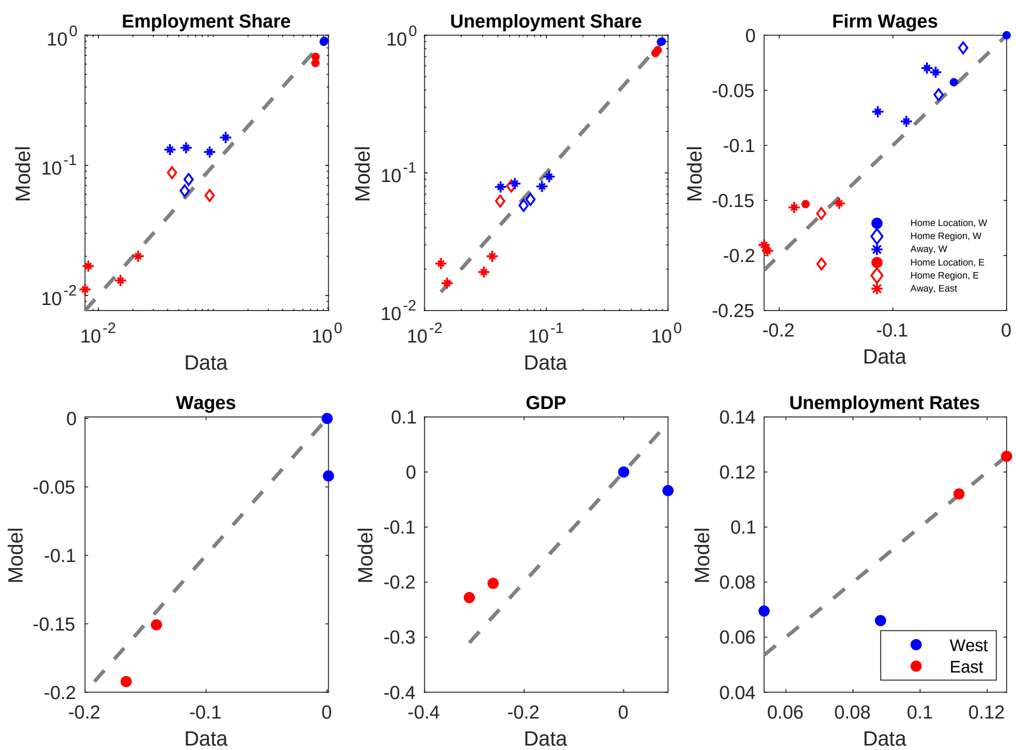
Notes: The left panel shows the average wage gains of different types of job-to-job moves in the data (x-axis) against the average wage gains in the model (y-axis) for the "All Moves" alternative. The right panel shows the frequency of each direction of the job-to-job move in the data (x-axis) against the frequency in the model (y-axis). Different types of moves are identified by a mix of colors and symbols, listed in the right panel. In total, there are 64 possible types of moves by (origin location, destination location, home location). The data moments used are listed in Supplemental Appendices Q.2.1 and Q.2.2. Gray symbols are moves within-region, blue symbols are moves to the West, and red symbols are moves to the East. Diamonds symbolize cross-location moves within-region back to the home location (in gray) or cross-region moves back to the home region (blue or red). Stars symbolize cross-location moves within-region away from the home location (in gray) or cross-region moves away from the home region (blue or red). Gray circles are moves within-location.

Figure S16: Employment, Wages, and GDP by Location and Worker-Type; Only Migration Moves



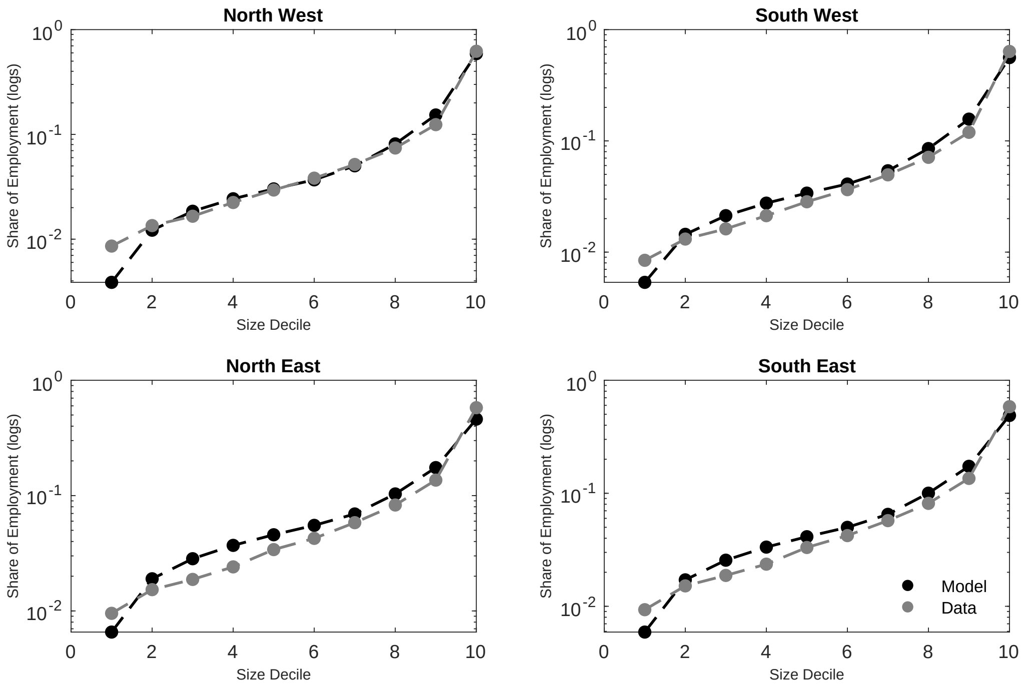
Notes: The figure graphs the value of various moments in the model against the same moments in the data for the “Only Migration Moves” estimation. The construction of these moments is described in Supplemental Appendices Q.2.3 to Q.2.8. Each dot corresponds to one moment. The top left panel shows the share of employed workers residing in each location, by worker type. The top middle panel shows the share of unemployed workers residing in each location, again by worker type. The top right panel shows the average log firm component of wages for each worker type residing in each location, normalized relative to workers whose home location is North-West and that are currently residing in the North-West. In each panel, moments relating to West German workers are in blue and moments for East German workers are in red. Circles are for workers currently residing in their home location, squares for workers residing in their home region but not location, and stars are for workers currently out of their home region. The bottom left panel shows the average log firm component of wages by location, relative to the North-West. The bottom middle panel shows the GDP per capita of each location relative to the North West. Last, the bottom right panel shows the unemployment rates. In each of these panels, West locations are in blue and East locations are in red.

Figure S17: Employment, Wages, and GDP by Location and Worker-Type; All Moves



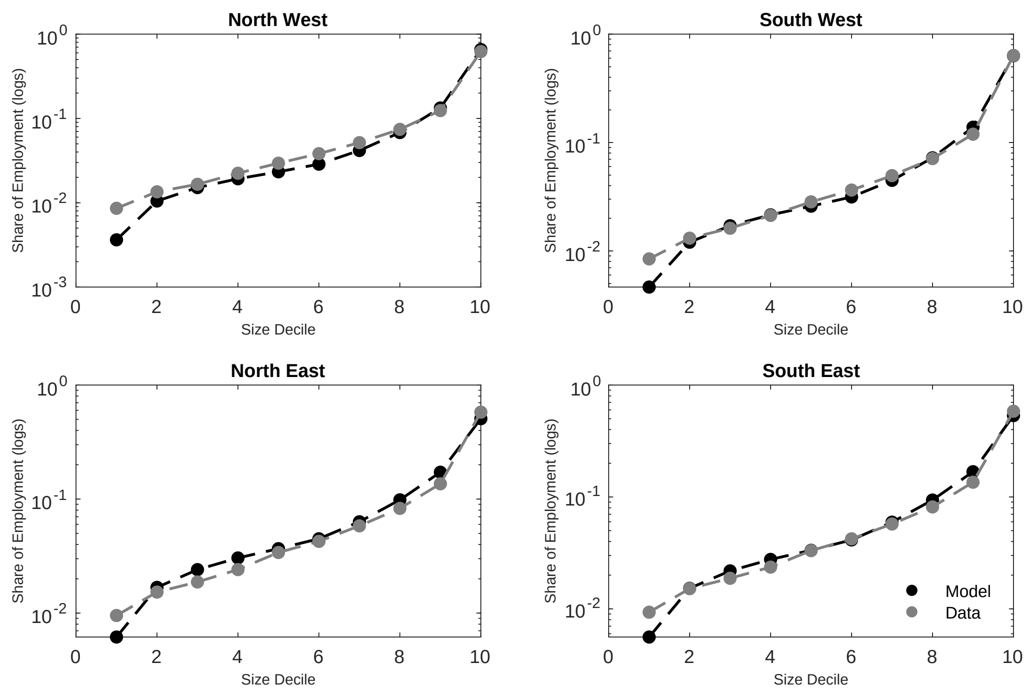
Notes: The figure graphs the value of various moments in the model against the same moments in the data for the "All Moves" estimation. The construction of these moments is described in Supplemental Appendices Q.2.3 to Q.2.8. Each dot corresponds to one moment. The top left panel shows the share of employed workers working in each location, by worker type. The top middle panel shows the share of unemployed workers receiving unemployment benefits in each location, again by worker type. The top right panel shows the average log firm component of wages for each worker type working in each location, normalized relative to workers whose home location is North-West and that are currently working in the North-West. In each panel, moments relating to West German workers are in blue and moments for East German workers are in red. Circles are for workers currently working in their home location, squares for workers working in their home region but not location, and stars are for workers currently out of their home region. The bottom left panel shows the average log firm component of wages by location, relative to the North-West. The bottom middle panel shows the GDP per capita of each location relative to the North West. Last, the bottom right panel shows the unemployment rates. In each of these panels, West locations are in blue and East locations are in red.

Figure S18: Within-region Firm-Size Distributions; Only Migration Moves



Notes: The figure compares the firm size distribution in the model and in the data for the "Only Migration Moves" estimation. Each panel graphs the share of total employment that is working at each decile of the firm size distribution for each of the four locations. Model moments are in black and data moments are in gray. The construction of these moments is described in Supplemental Appendix Q.2.9.

Figure S19: Within-region Firm-Size Distributions; All Moves



Notes: The figure compares the firm size distribution in the model and in the data for the "All Moves" estimation. Each panel graphs the share of total employment that is working at each decile of the firm size distribution for each of the four locations. Model moments are in black and data moments are in gray. The construction of these moments is described in Supplemental Appendix Q.2.9.

Table S33: Model Fit for Additional Moments; Only Migration Moves

	Parameters		Model		Data	
			West	*East*	*West*	*East*
(1)	Slopes wage vs firm's size, by j	*North*	0.128	0.139	0.124	0.110
		South	0.173	0.146	0.124	0.109
(2)	Slopes separation vs firm's wage, by j	*North*	-0.018	-0.015	-0.029	-0.037
		South	-0.018	-0.015	-0.033	-0.036
(3)	Slopes wage gain vs firm's wage, by j	*North*	-0.832	-0.910	-0.549	-0.561
		South	-0.851	-0.893	-0.577	-0.562
(4)	Average Std of job-job wage gains, by j	*North*	0.439	0.417	0.609	0.647
		South	0.445	0.421	0.631	0.578
(5)	Profit shares, by j	*North*	0.325	0.407	0.274	0.299
		South	0.345	0.387	0.259	0.263

Notes: The table compares several moments in the model to their data analogues by location of the firm. The construction of these moments is described in Supplemental Appendices Q.2.10 to Q.2.14. The first row shows the slope of the wage function with respect to firm size. The second row presents the slope of the separation rate with respect to firms' wage. The third row shows the slope of the average wage gain from a job-to-job move as a function of the origin firm's wage. The fourth row presents the standard deviation of wage gains from a job-to-job move by location of the origin firm. We take the average across all the 16 possible job-to-job moves that originated in each region. All the 64 disaggregated moments are included in Supplemental Appendix U. The last row shows the average ratio of profits to labor costs in each location.

Table S34: Model Fit for Additional Moments; All Moves

	Parameters		Model		Data	
			West	*East*	*West*	*East*
(1)	Slopes wage vs firm's size, by j	*North*	0.134	0.146	0.124	0.110
		South	0.167	0.149	0.124	0.109
(2)	Slopes separation vs firm's wage, by j	*North*	-0.032	-0.024	-0.029	-0.037
		South	-0.032	-0.025	-0.033	-0.036
(3)	Slopes wage gain vs firm's wage, by j	*North*	-0.739	-0.838	-0.549	-0.561
		South	-0.759	-0.821	-0.577	-0.562
(4)	Average Std of job-job wage gains, by j	*North*	0.403	0.391	0.546	0.527
		South	0.408	0.391	0.561	0.523
(5)	Profit shares, by j	*North*	0.251	0.328	0.274	0.299
		South	0.265	0.313	0.259	0.263

Notes: The table compares several moments in the model to their data analogues by location of the firm. The construction of these moments is described in Supplemental Appendices Q.2.10 to Q.2.14. The first row shows the slope of the wage function with respect to firm size. The second row presents the slope of the separation rate with respect to firms' wage. The third row shows the slope of the average wage gain from a job-to-job move as a function of the origin firm's wage. The fourth row presents the standard deviation of wage gains from a job-to-job move by location of the origin firm. We take the average across all the 16 possible job-to-job moves that originated in each region. All the 64 disaggregated moments are included in Supplemental Appendix U. The last row shows the average ratio of profits to labor costs in each location.

Table S35: Estimated Spatial Frictions; Only Migration Moves

Moving Costs $\{\kappa\}$			
(1)	Moving cost as share of PDV of income: $\kappa_0 e^{\kappa_1 dist_{jx}}$ (b/w closest to b/w furthest locations)		8.49% to 8.97%
Preferences $\{\tau\}$			
(2)	Cost of not living in the home location but in the home region, as share of income: τ_l		10.26%
(3)	Cost of not living in the home region, as share of income: τ_r		12.89%
Relative Search Efficiency $\{z\}$			
(4)	w/i location, away from home location: $1 - z_{l,1}$		91.59%
		5.i) not to home region: $z_0 e^{-z_1 dist_{jx}}$	6.23% to 6.03%
(5)	b/w locations (closest to furthest locations)	5.ii) to home region: $\left(z_0 e^{-z_1 dist_{jx}}\right)(1 + z_r)$	7.07% to 6.72%
		5.iii) to home location: $\left(z_0 e^{-z_1 dist_{jx}}\right)\left(1 + z_{l,2}\right)$	16.53% to 15.71%

Notes: The table shows the estimated values of the spatial frictions in the "Only Migration Moves" estimation. All parameters used to compute them, according to the formula included in each row, are in Table S37. Row 1 provides a range of the estimated moving costs, ranging from costs for moves between the closest two locations to moves between the furthest two locations. Rows 2-3 present the values of the estimated preference parameters. Search efficiencies in rows 4 and 5 are expressed as a percentage of the efficiency within the home location, z^j_{jj}, which is normalized to 1. Rows 5i-5iii show the efficiencies for searching across locations outside of the home region, in the home region but not the home location, and in the home location, respectively. The efficiencies are again reported as a range for searching between the two closest locations to searching between the two furthest locations.

Table S37: All Estimated Parameters, Only Migration Moves

(1)	τ_{SW}: amenity SW	0.990	(12)	A_{SW}: productivity SW	1.034
(2)	τ_E: amenity East	1.120	(13)	A_E: productivity East	0.943
(3)	τ_r: region preference	0.103	(14)	$\xi_{0,W}$: vacancy cost West	0.265
(4)	τ_l: location preference	0.129	(15)	$\xi_{0,E}$: vacancy cost East	0.346
(5)	κ_0: move cost out of location	0.088	(16)	ξ_1: vacancy curvature	1.104
(6)	κ_1: move cost distance	0.078	(17)	σ: variance of taste shocks	0.057
(7)	z_0: search out of location	0.067	(18)	Σ: variance p distribution	0.328
(8)	z_1: search distance	-0.071	(19)	ν: search intensity of unemployed	6.691
(9)	$z_{l,1}$: search in home location	0.092	(20)	ϵ: curvature search cost	6.669
(10)	$z_{l,2}$: search to home location	1.385	(21)	ι: workers' outside option	0.977
(11)	z_r: search to home region	0.114			

Notes: The table reports the 21 parameters estimated from our model for the "Only Migration Moves" estimation, estimated according to the procedure described in Appendix G.

Table S36: Estimated Spatial Frictions; All Moves

Moving Costs $\{\kappa\}$			
(1)	Moving cost as share of PDV of income: $\kappa_0 e^{\kappa_1 dist_{jx}}$ (b/w closest to b/w furthest locations)		0.46% to 1.52%
Preferences $\{\tau\}$			
(2)	Cost of not living in the home location but in the home region, as share of income: τ_l		10.37%
(3)	Cost of not living in the home region, as share of income: τ_r		13.34%
Relative Search Efficiency $\{z\}$			
(4)	w/i location, away from home location: $1 - z_{l,1}$		81.26%
		5.i) not to home region: $z_0 e^{-z_1 dist_{jx}}$	6.68% to 6.03%
(5)	b/w locations (closest to furthest locations)	5.ii) to home region: $\left(z_0 e^{-z_1 dist_{jx}}\right)(1 + z_r)$	9.52% to 8.06%
		5.iii) to home location: $\left(z_0 e^{-z_1 dist_{jx}}\right)\left(1 + z_{l,2}\right)$	55.60% to 47.07%

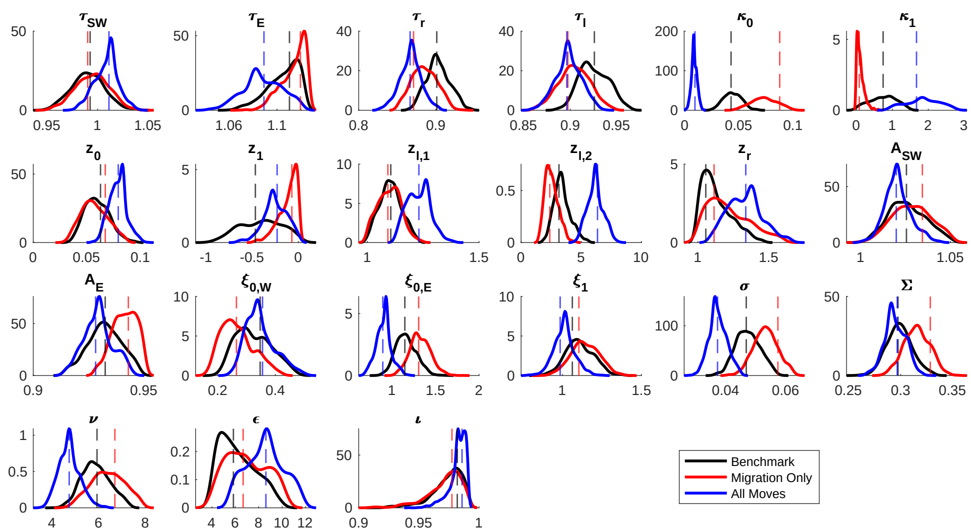
Notes: The table shows the estimated values of the spatial frictions in the "All Moves" estimation. All parameters used to compute them, according to the formula included in each row, are in Table S38. Row 1 provides a range of the estimated moving costs, ranging from costs for moves between the closest two locations to moves between the furthest two locations. Rows 2-3 present the values of the estimated preference parameters. Search efficiencies in rows 4 and 5 are expressed as a percentage of the efficiency within the home location, z^j_{jj}, which is normalized to 1. Rows 5i-5iii show the efficiencies for searching across locations outside of the home region, in the home region but not the home location, and in the home location, respectively. The efficiencies are again reported as a range for searching between the two closest locations to searching between the two furthest locations.

Table S38: All Estimated Parameters, All Moves

(1)	τ_{SW}: amenity SW	1.011	(12)	A_{SW}: productivity SW	1.020
(2)	τ_E: amenity East	1.089	(13)	A_E: productivity East	0.928
(3)	τ_r: region preference	0.104	(14)	$\xi_{0,W}$: vacancy cost West	0.355
(4)	τ_l: location preference	0.133	(15)	$\xi_{0,E}$: vacancy cost East	0.317
(5)	κ_0: move cost out of location	0.009	(16)	ξ_1: vacancy curvature	0.985
(6)	κ_1: move cost distance	1.672	(17)	σ: variance of taste shocks	0.037
(7)	z_0: search out of location	0.079	(18)	Σ: variance p distribution	0.297
(8)	z_1: search distance	-0.232	(19)	ν: search intensity of unemployed	4.733
(9)	$z_{l,1}$: search in home location	0.231	(20)	ϵ: curvature search cost	8.613
(10)	$z_{l,2}$: search to home location	5.348	(21)	ι: workers' outside option	0.986
(11)	z_r: search to home region	0.338			

Notes: The table reports the 21 parameters estimated from our model for the "All Moves" estimation, estimated according to the procedure described in Appendix G.

Figure S20: Comparison of the Outcomes of the Three Estimations



Notes: The figure compares the outcomes of the three estimation alternatives. Each panel shows a different one of the 21 estimated parameters. For each parameter, we show the estimated density for the three estimations. Black is the benchmark estimation. Red is the "Only Migration Moves" estimation. Blue is the "All Moves" estimation. The vertical lines are our estimated parameter values. The top row shows the estimation results for τ_{SW}, τ_E, τ_r, τ_l, κ_0 and κ_1. The second row shows the results for z_0, z_1, $z_{l,1}$, $z_{l,2}$, z_r, and A_{SW}. The third row shows the estimates for A_E, $\xi_{0,W}$, $\xi_{0,E}$, ξ_1, σ, and Σ. The last row shows the estimates for ν, ϵ, and ι.

U Model Fit, All Details

In this section, we provide a comparison between the empirical targets and the model-simulated moments for each one of the 305 targeted moments summarized in Table 4 and each one of the three estimations described in Supplemental Appendix T. Each group of moments in a row of Table 4 is presented in one subsection. The order of the subsections follows the order of the moments in the table.

Finally, the last subsection includes plots of the draws of the likelihood functions from our final estimation chain plotted against the parameter estimates. The figure shows that the likelihoods are mostly, and especially for the core spatial friction parameters, single-peaked and with the peak corresponding to our estimates.

U.1 Wage Gains of Job-to-Job Movers

Table S39: Average Log Wage Gains for Job-Job Movers by Birth and Migration Locations – Benchmark

Move to Location:		NW		SW		NE		SE	
Birth Location	Current Work Location	Data	Model	Data	Model	Data	Model	Data	Model
NW	NW	0.109	0.115	0.282	0.280	0.136	0.165	0.244	0.210
	SW	0.195	0.093	0.090	0.082	0.048	0.118	0.108	0.126
	NE	0.127	0.118	0.206	0.210	0.051	0.058	0.075	0.136
	SE	0.164	0.100	0.219	0.171	0.202	0.095	0.072	0.068
SW	NW	0.100	0.091	0.169	0.074	0.120	0.096	0.134	0.113
	SW	0.281	0.311	0.107	0.105	0.280	0.194	0.186	0.213
	NE	0.260	0.192	0.139	0.104	0.049	0.059	0.029	0.117
	SE	0.152	0.197	0.161	0.080	0.130	0.107	0.085	0.067
NE	NW	0.081	0.084	0.150	0.151	0.031	-0.011	0.101	0.066
	SW	0.177	0.175	0.082	0.077	-0.020	0.015	0.097	0.070
	NE	0.236	0.309	0.283	0.300	0.057	0.082	0.168	0.199
	SE	0.270	0.226	0.276	0.203	0.076	0.045	0.094	0.075
SE	NW	0.085	0.080	0.189	0.134	0.065	0.031	0.044	0.004
	SW	0.207	0.183	0.072	0.072	0.052	0.067	0.034	0.019
	NE	0.153	0.238	0.176	0.224	0.045	0.060	0.112	0.083
	SE	0.325	0.298	0.269	0.260	0.111	0.150	0.091	0.093

Notes: The table shows the average wage gains of job movers by origin location-destination location-home location. Empirical moments are computed as described in Supplemental Appendix Q.2.1, using the benchmark definition of moves.

Table S40: Average Log Wage Gains for Job-Job Movers by Birth and Migration Locations – Only Migration Moves

Move to Location:		NW		SW		NE		SE	
Birth Location	Current Work Location	Data	Model	Data	Model	Data	Model	Data	Model
NW	NW	0.110	0.117	0.325	0.318	0.160	0.178	0.276	0.238
	SW	0.214	0.126	0.090	0.082	0.048	0.135	0.122	0.177
	NE	0.173	0.159	0.206	0.255	0.052	0.058	0.218	0.202
	SE	0.182	0.141	0.237	0.237	0.074	0.145	0.074	0.069
SW	NW	0.099	0.089	0.182	0.097	0.118	0.107	0.167	0.152
	SW	0.357	0.366	0.107	0.108	0.290	0.198	0.270	0.253
	NE	0.338	0.270	0.151	0.139	0.052	0.057	0.053	0.195
	SE	0.170	0.258	0.145	0.120	0.114	0.141	0.086	0.068
NE	NW	0.080	0.080	0.147	0.173	0.023	-0.009	0.130	0.101
	SW	0.185	0.223	0.081	0.074	-0.019	0.014	0.102	0.121
	NE	0.327	0.378	0.295	0.342	0.057	0.082	0.355	0.266
	SE	0.292	0.275	0.312	0.243	0.070	0.066	0.096	0.073
SE	NW	0.085	0.076	0.203	0.167	0.023	0.058	0.055	0.011
	SW	0.211	0.222	0.071	0.070	0.028	0.085	0.039	0.032
	NE	0.150	0.288	0.193	0.257	0.046	0.059	0.143	0.107
	SE	0.374	0.362	0.384	0.321	0.147	0.195	0.092	0.093

Notes: The table shows the average wage gains of job movers by origin location-destination location-home location. Empirical moments are computed as described in Supplemental Appendix Q.2.1, using the "Only Migration Moves" alternative.

Table S41: Average Log Wage Gains for Job-Job Movers by Birth and Migration Locations – All Moves

Move to Location:		NW		SW		NE		SE	
Birth Location	Current Work Location	Data	Model	Data	Model	Data	Model	Data	Model
NW	NW	0.109	0.127	0.195	0.189	0.098	0.120	0.141	0.144
	SW	0.148	0.095	0.090	0.077	0.077	0.072	0.078	0.073
	NE	0.097	0.112	0.030	0.135	0.052	0.048	0.075	0.080
	SE	0.100	0.097	0.145	0.102	0.094	0.047	0.074	0.057
SW	NW	0.099	0.080	0.092	0.046	0.070	0.044	0.066	0.044
	SW	0.231	0.229	0.107	0.120	0.161	0.161	0.121	0.149
	NE	0.133	0.126	0.093	0.079	0.052	0.043	0.009	0.055
	SE	0.116	0.141	0.102	0.073	0.087	0.066	0.086	0.057
NE	NW	0.080	0.091	0.094	0.105	0.049	0.016	0.082	0.050
	SW	0.147	0.132	0.081	0.085	0.031	0.041	0.126	0.058
	NE	0.181	0.213	0.170	0.208	0.057	0.097	0.140	0.140
	SE	0.195	0.161	0.172	0.139	0.048	0.055	0.096	0.079
SE	NW	0.085	0.085	0.108	0.084	0.048	0.021	0.055	0.021
	SW	0.176	0.144	0.071	0.082	0.059	0.062	0.035	0.046
	NE	0.116	0.170	0.070	0.149	0.046	0.064	0.059	0.080
	SE	0.233	0.210	0.218	0.174	0.095	0.112	0.092	0.107

Notes: The table shows the average wage gains of job movers by origin location-destination location-home location. Empirical moments are computed as described in Supplemental Appendix Q.2.1, using the "All Moves" alternative.

U.2 Flows of Job-to-Job Movers

Table S42: Job-to-Job Migration Flows Between Locations by Birth Location – Benchmark

Move to Location:		NW		SW		NE		SE	
Birth Location	Work Location	Data	Model	Data	Model	Data	Model	Data	Model
NW	NW	0.977%	1.172%	0.020%	0.006%	0.004%	0.003%	0.002%	0.004%
	SW	0.208%	0.208%	1.094%	1.173%	0.006%	0.008%	0.009%	0.017%
	NE	0.194%	0.346%	0.030%	0.032%	0.948%	1.039%	0.028%	0.038%
	SE	0.133%	0.305%	0.068%	0.041%	0.041%	0.025%	1.057%	0.952%
SW	NW	0.983%	1.047%	0.215%	0.153%	0.007%	0.008%	0.007%	0.012%
	SW	0.025%	0.011%	1.244%	1.324%	0.001%	0.002%	0.006%	0.007%
	NE	0.084%	0.056%	0.133%	0.273%	0.881%	1.041%	0.074%	0.044%
	SE	0.033%	0.041%	0.159%	0.311%	0.027%	0.022%	1.111%	0.958%
NE	NW	1.054%	1.094%	0.032%	0.018%	0.077%	0.120%	0.011%	0.021%
	SW	0.073%	0.028%	1.247%	1.228%	0.069%	0.115%	0.029%	0.031%
	NE	0.043%	0.023%	0.010%	0.013%	0.911%	1.190%	0.031%	0.026%
	SE	0.038%	0.031%	0.047%	0.030%	0.124%	0.202%	1.006%	0.981%
SE	NW	1.031%	1.100%	0.089%	0.020%	0.019%	0.018%	0.094%	0.145%
	SW	0.043%	0.026%	1.179%	1.238%	0.010%	0.015%	0.117%	0.188%
	NE	0.031%	0.037%	0.030%	0.025%	0.608%	1.067%	0.138%	0.272%
	SE	0.011%	0.017%	0.033%	0.018%	0.020%	0.016%	1.080%	1.103%

Notes: The table presents the share of employed workers that make a job-to-job move for each triplet of home location, current location, and destination location in an average month. Empirical moments are computed as described in Supplemental Appendix Q.2.2, using the benchmark definition of moves.

Table S43: Job-to-Job Migration Flows Between Locations by Birth Location – Only Migration Moves

Move to Location:		NW		SW		NE		SE	
Birth Location	Work Location	Data	Model	Data	Model	Data	Model	Data	Model
NW	NW	0.977%	1.109%	0.014%	0.004%	0.002%	0.001%	0.001%	0.002%
	SW	0.182%	0.147%	1.093%	1.128%	0.006%	0.007%	0.007%	0.010%
	NE	0.106%	0.219%	0.029%	0.032%	0.947%	1.025%	0.008%	0.019%
	SE	0.113%	0.190%	0.051%	0.027%	0.016%	0.012%	1.056%	0.961%
SW	NW	0.983%	1.014%	0.191%	0.115%	0.006%	0.006%	0.006%	0.008%
	SW	0.014%	0.007%	1.244%	1.242%	0.001%	0.002%	0.002%	0.003%
	NE	0.060%	0.039%	0.127%	0.205%	0.879%	1.028%	0.024%	0.020%
	SE	0.024%	0.031%	0.085%	0.183%	0.010%	0.012%	1.110%	0.964%
NE	NW	1.052%	1.053%	0.029%	0.017%	0.065%	0.089%	0.009%	0.017%
	SW	0.065%	0.022%	1.247%	1.173%	0.069%	0.099%	0.027%	0.021%
	NE	0.017%	0.011%	0.009%	0.009%	0.911%	1.147%	0.005%	0.010%
	SE	0.034%	0.022%	0.035%	0.021%	0.062%	0.108%	1.002%	0.982%
SE	NW	1.030%	1.057%	0.077%	0.017%	0.015%	0.013%	0.084%	0.107%
	SW	0.036%	0.021%	1.178%	1.178%	0.009%	0.015%	0.093%	0.124%
	NE	0.019%	0.027%	0.024%	0.024%	0.604%	1.045%	0.061%	0.152%
	SE	0.007%	0.008%	0.015%	0.007%	0.004%	0.005%	1.080%	1.084%

Notes: The table presents the share of employed workers that make a job-to-job move for each triplet of home location, current location, and destination location in an average month. Empirical moments are computed as described in Supplemental Appendix Q.2.2, using the "Only Migration Moves" alternative.

Table S44: Job-to-Job Migration Flows Between Locations by Birth Location – All Moves

Move to Location:		NW		SW		NE		SE	
Birth Location	Work Location	Data	Model	Data	Model	Data	Model	Data	Model
NW	NW	0.977%	1.321%	0.047%	0.042%	0.009%	0.014%	0.004%	0.016%
	SW	0.671%	0.802%	1.097%	1.225%	0.024%	0.022%	0.026%	0.033%
	NE	0.543%	1.252%	0.098%	0.117%	0.953%	0.939%	0.057%	0.063%
	SE	0.485%	1.147%	0.176%	0.129%	0.102%	0.049%	1.064%	0.899%
SW	NW	0.989%	1.119%	0.879%	0.723%	0.024%	0.021%	0.024%	0.029%
	SW	0.056%	0.051%	1.244%	1.458%	0.004%	0.011%	0.011%	0.022%
	NE	0.215%	0.148%	0.591%	1.164%	0.892%	0.933%	0.161%	0.072%
	SE	0.091%	0.120%	0.465%	1.187%	0.052%	0.042%	1.117%	0.906%
NE	NW	1.056%	1.160%	0.087%	0.051%	0.384%	0.375%	0.035%	0.048%
	SW	0.197%	0.065%	1.251%	1.262%	0.329%	0.371%	0.093%	0.059%
	NE	0.076%	0.077%	0.033%	0.061%	0.911%	1.147%	0.041%	0.072%
	SE	0.103%	0.083%	0.129%	0.083%	0.659%	0.606%	1.009%	0.904%
SE	NW	1.035%	1.175%	0.240%	0.057%	0.070%	0.043%	0.456%	0.452%
	SW	0.104%	0.061%	1.181%	1.290%	0.031%	0.039%	0.495%	0.513%
	NE	0.083%	0.093%	0.100%	0.081%	0.610%	0.952%	0.612%	0.778%
	SE	0.028%	0.064%	0.066%	0.068%	0.028%	0.052%	1.080%	1.099%

Notes: The table presents the share of employed workers that make a job-to-job move for each triplet of home location, current location, and destination location in an average month. Empirical moments are computed as described in Supplemental Appendix Q.2.2, using the "All Moves" alternative.

U.3 Employment Share

Table S45: Share of Employed Workers by Residence Location – Benchmark

Birth Location	Current Location	Share Residing in Current Location: Data	Model
NW	NW	92.7%	94.1%
	SW	4.4%	3.6%
	NE	2.0%	0.9%
	SE	0.8%	1.4%
SW	NW	4.3%	7.3%
	SW	92.5%	89.6%
	NE	0.8%	0.9%
	SE	2.3%	2.2%
NE	NW	7.6%	15.9%
	SW	4.3%	10.5%
	NE	84.7%	64.2%
	SE	3.4%	9.4%
SE	NW	3.0%	12.2%
	SW	6.7%	10.0%
	NE	2.5%	5.4%
	SE	87.7%	72.4%

Notes: The table shows the fraction of employed workers of the home location indicated in column 1 that live in the location indicated in column 2. Empirical moments are computed as described in Supplemental Appendix Q.2.3.

Table S46: Share of Employed Workers by Residence Location – Only Migration Moves

Birth Location	Current Location	Share Residing in Current Location: Data	Model
NW	NW	92.7%	95.2%
	SW	4.4%	3.2%
	NE	2.0%	0.6%
	SE	0.8%	1.0%
SW	NW	4.3%	6.1%
	SW	92.5%	91.6%
	NE	0.8%	0.9%
	SE	2.3%	1.5%
NE	NW	7.6%	11.9%
	SW	4.3%	9.3%
	NE	84.7%	71.2%
	SE	3.4%	7.6%
SE	NW	3.0%	8.3%
	SW	6.7%	6.8%
	NE	2.5%	3.5%
	SE	87.7%	81.4%

Notes: The table shows the fraction of employed workers of the home location indicated in column 1 that live in the location indicated in column 2. Empirical moments are computed as described in Supplemental Appendix Q.2.3.

Table S47: Share of Employed Workers by Working Location – All Moves

Birth Location	Current Location	Share Working in Current Location: Data	Model
NW	NW	92.0%	90.6%
	SW	5.6%	6.4%
	NE	1.6%	1.3%
	SE	0.8%	1.7%
SW	NW	6.1%	7.8%
	SW	90.9%	89.1%
	NE	0.8%	1.1%
	SE	2.2%	2.0%
NE	NW	12.8%	16.4%
	SW	5.8%	13.7%
	NE	77.1%	61.2%
	SE	4.4%	8.8%
SE	NW	4.2%	13.2%
	SW	9.3%	12.7%
	NE	9.3%	5.9%
	SE	77.3%	68.2%

Notes: The table shows the fraction of employed workers of the home location indicated in column 1 that work in the location indicated in column 2. Empirical moments are computed as described in Supplemental Appendix Q.2.3.

U.4 Unemployment Share

Table S48: Share of Unemployed Workers by Residence Location – Benchmark

Birth Location	Current Location	Share Residing in Current Location: Data	Model
NW	NW	90.9%	92.7%
	SW	4.5%	3.6%
	NE	3.3%	1.5%
	SE	1.3%	2.1%
SW	NW	4.7%	6.9%
	SW	90.2%	88.3%
	NE	1.5%	1.6%
	SE	3.6%	3.2%
NE	NW	4.9%	10.0%
	SW	2.9%	6.9%
	NE	89.5%	73.8%
	SE	2.7%	9.3%
SE	NW	2.4%	8.0%
	SW	4.8%	6.7%
	NE	2.9%	6.2%
	SE	90.0%	79.1%

Notes: The table shows the fraction of unemployed workers of the home location indicated in column 1 that live in the location indicated in column 2. Empirical moments are computed as described in Supplemental Appendix Q.2.4.

Table S49: Share of Unemployed Workers by Residence Location – Only Migration Moves

		Share Residing in Current Location	
Birth Location	Current Location	Data	Model
NW	NW	90.9%	94.1%
	SW	4.5%	3.2%
	NE	3.3%	1.1%
	SE	1.3%	1.6%
SW	NW	4.7%	5.9%
	SW	90.2%	90.4%
	NE	1.5%	1.5%
	SE	3.6%	2.2%
NE	NW	4.9%	7.4%
	SW	2.9%	6.0%
	NE	89.5%	79.1%
	SE	2.7%	7.6%
SE	NW	2.4%	5.5%
	SW	4.8%	4.6%
	NE	2.9%	4.1%
	SE	90.0%	85.9%

Notes: The table shows the fraction of unemployed workers of the home location indicated in column 1 that live in the location indicated in column 2. Empirical moments are computed as described in Supplemental Appendix Q.2.4.

Table S50: Share of Unemployed Workers by Location of Last Job – All Moves

Birth Location	Current Location	Share with Last Job in Current Location: Data	Model
NW	NW	89.1%	90.1%
	SW	6.5%	5.8%
	NE	3.1%	1.9%
	SE	1.4%	2.2%
SW	NW	7.4%	6.4%
	SW	87.5%	89.5%
	NE	1.5%	1.6%
	SE	3.6%	2.5%
NE	NW	10.6%	9.4%
	SW	5.5%	8.4%
	NE	78.8%	74.2%
	SE	5.2%	8.0%
SE	NW	4.2%	7.9%
	SW	9.2%	8.0%
	NE	4.2%	6.2%
	SE	82.4%	77.9%

Notes: The table shows the fraction of unemployed workers of the home location indicated in column 1 whose last job was in the location indicated in column 2. Empirical moments are computed as described in Supplemental Appendix Q.2.4.

U.5 Firm Component of Wages by Location and Worker Type

Table S51: Firm Fixed Effects by the Birth and Residence Location of Workers – Benchmark

Birth Location	Current Live Location	Data	Model
NW	SW	-0.064	-0.039
	NE	-0.141	-0.173
	SE	-0.139	-0.119
SW	NW	-0.036	0.004
	SW	-0.046	-0.047
	NE	-0.193	-0.174
	SE	-0.165	-0.122
NE	NW	-0.090	-0.013
	SW	-0.104	-0.059
	NE	-0.198	-0.189
	SE	-0.119	-0.136
SE	NW	-0.056	-0.014
	SW	-0.090	-0.062
	NE	-0.171	-0.188
	SE	-0.169	-0.140

Notes: The table shows the estimated coefficients β_{hl} in specification (56) in Supplemental Appendix Q.2.5 for workers with home location h indicated in column 1 and residence location l indicated in column 2. Each of the coefficients is relative to the coefficient of workers born in the Northwest and living in the Northwest.

Table S52: Firm Fixed Effects by the Birth and Current Residence Location of Workers – Only Migration Moves

Birth Location	Current Live Location	Data	Model
NW	SW	-0.064	-0.040
	NE	-0.141	-0.183
	SE	-0.139	-0.126
SW	NW	-0.036	0.002
	SW	-0.046	-0.045
	NE	-0.193	-0.185
	SE	-0.165	-0.128
NE	NW	-0.090	-0.015
	SW	-0.104	-0.060
	NE	-0.198	-0.197
	SE	-0.119	-0.140
SE	NW	-0.056	-0.017
	SW	-0.090	-0.062
	NE	-0.171	-0.196
	SE	-0.169	-0.144

Notes: The table shows the estimated coefficients β_{hl} in specification (56) in Supplemental Appendix Q.2.5 for workers with home location h indicated in column 1 and residence location l indicated in column 2. Each of the coefficients is relative to the coefficient of workers born in the Northwest and living in the Northwest.

Table S53: Firm Fixed Effects by the Birth and Current Work Location of Workers – All Moves

Birth Location	Current Work Location	Data	Model
NW	SW	-0.060	-0.054
	NE	-0.210	-0.196
	SE	-0.147	-0.153
SW	NW	-0.038	-0.011
	SW	-0.046	-0.043
	NE	-0.213	-0.190
	SE	-0.187	-0.156
NE	NW	-0.070	-0.030
	SW	-0.113	-0.069
	NE	-0.211	-0.195
	SE	-0.163	-0.162
SE	NW	-0.062	-0.034
	SW	-0.088	-0.078
	NE	-0.163	-0.208
	SE	-0.177	-0.153

Notes: The table shows the estimated coefficients β_{hl} in specification (56) in Supplemental Appendix Q.2.5 for workers with home location h indicated in column 1 and work location l indicated in column 2. Each of the coefficients is relative to the coefficient of workers born in the Northwest and working in the Northwest.

U.6 Firm Component of Wages by Firm Location

Table S54: Firm Fixed Effect by Location – Benchmark

	(1)	(2)
Location	Data	Model
NW	0	0
SW	0.001	-0.046
NE	-0.166	-0.187
SE	-0.141	-0.136

Notes: The table presents the estimated coefficients β_l from specification (57) in Supplemental Appendix Q.2.6 for firm location l indicated in column 1, where NW is the omitted category.

Table S55: Firm Fixed Effect by Location – Migration Moves

	(1)	(2)
Location	Data	Model
NW	0	0
SW	0.001	-0.045
NE	-0.166	-0.195
SE	-0.141	-0.141

Notes: The table presents the estimated coefficients β_l from specification (57) in Supplemental Appendix Q.2.6 for firm location l indicated in column 1, where NW is the omitted category.

Table S56: Firm Fixed Effect by Location – All Moves

	(1)	(2)
Location	Data	Model
NW	0	0
SW	0.001	-0.042
NE	-0.166	-0.192
SE	-0.141	-0.151

Notes: The table presents the estimated coefficients β_l from specification (57) in Supplemental Appendix Q.2.6 for firm location l indicated in column 1, where NW is the omitted category.

U.7 GDP per Capita

Table S57: GDP per capita by Location – Benchmark

	Avg. GDP pc, normalized to 1	
Location	Data	Model
NW	1	1
SW	1.093	0.971
NE	0.733	0.806
SE	0.769	0.828

Notes: The table shows the GDPpc of each location. The empirical moments are computed as described in Supplemental Appendix Q.2.7. We obtain nominal GDPpc from the National Accounts of the States (Volkswirtschaftliche Gesamtrechnungen der Länder, VGRdL), and construct price deflators from the inflation rates reported in the VGRdL and from the price levels obtained from the survey of the Federal Institute for Building, Urban Affairs and Spatial Development (BBSR).

Table S58: GDP per capita by Location – Only Migration Moves

	Avg. GDP pc, normalized to 1	
Location	Data	Model
NW	1	1
SW	1.093	0.977
NE	0.733	0.809
SE	0.769	0.829

Notes: The table shows the GDPpc of each location. The empirical moments are computed as described in Supplemental Appendix Q.2.7. We obtain nominal GDPpc from the National Accounts of the States (Volkswirtschaftliche Gesamtrechnungen der Länder, VGRdL), and construct price deflators from the inflation rates reported in the VGRdL and from the price levels obtained from the survey of the Federal Institute for Building, Urban Affairs and Spatial Development (BBSR).

Table S59: GDP per capita by Location – All Moves

	Avg. GDP pc, normalized to 1	
Location	Data	Model
NW	1	1
SW	1.093	0.967
NE	0.733	0.796
SE	0.769	0.817

Notes: The table shows the GDPpc of each location. The empirical moments are computed as described in Supplemental Appendix Q.2.7. We obtain nominal GDPpc from the National Accounts of the States (Volkswirtschaftliche Gesamtrechnungen der Länder, VGRdL), and construct price deflators from the inflation rates reported in the VGRdL and from the price levels obtained from the survey of the Federal Institute for Building, Urban Affairs and Spatial Development (BBSR).

U.8 Unemployment Rate

Table S60: Share of Unemployed Workers by Location – Benchmark

	Unemployment Share	
Location	Data	Model
NW	8.82%	7.05%
SW	5.35%	7.25%
NE	12.58%	12.40%
SE	11.16%	11.31%

Note: The table shows the average unemployment rate in each location. The empirical moments are computed as described in Supplemental Appendix Q.2.8 from the official unemployment statistics of the German Federal Employment Agency.

Table S61: Share of Unemployed Workers by Location – Only Migration Moves

	Unemployment Share	
Location	Data	Model
NW	8.82%	7.23%
SW	5.35%	7.45%
NE	12.58%	12.59%
SE	11.16%	11.46%

Note: The table shows the average unemployment rate in each location. The empirical moments are computed as described in Supplemental Appendix Q.2.8 from the official unemployment statistics of the German Federal Employment Agency.

Table S62: Share of Unemployed Workers by Location – All Moves

	Unemployment Share	
Location	Data	Model
NW	8.82%	6.60%
SW	5.35%	6.95%
NE	12.58%	12.57%
SE	11.16%	11.20%

Note: The table shows the average unemployment rate in each location. The empirical moments are computed as described in Supplemental Appendix Q.2.8 from the official unemployment statistics of the German Federal Employment Agency.

U.9 Labor Share for Each Decile of Firm Size Distribution

Table S63: Share of Workers by Firm Size Decile and Location – Benchmark

	NW		SW		NE		SE	
Decile	Data	Model	Data	Model	Data	Model	Data	Model
1	0.009	0.004	0.008	0.005	0.010	0.007	0.009	0.006
2	0.013	0.012	0.013	0.014	0.015	0.018	0.015	0.016
3	0.017	0.017	0.016	0.020	0.019	0.027	0.019	0.024
4	0.022	0.022	0.021	0.025	0.024	0.035	0.024	0.031
5	0.029	0.027	0.028	0.031	0.034	0.042	0.033	0.038
6	0.038	0.033	0.036	0.037	0.043	0.051	0.042	0.046
7	0.052	0.048	0.050	0.051	0.058	0.067	0.057	0.063
8	0.074	0.078	0.071	0.082	0.083	0.103	0.081	0.099
9	0.124	0.150	0.119	0.154	0.136	0.176	0.135	0.174
10	0.622	0.609	0.636	0.580	0.578	0.473	0.584	0.503

Notes: Each column of the table shows the share of the location's workers employed at firms in the decile of the location's firm size distribution indicated in column 1. The empirical moments are computed as described in Supplemental Appendix Q.2.9.

Table S64: Share of Workers by Firm Size Decile and Location – Only Migration Moves

	NW		SW		NE		SE	
Decile	Data	Model	Data	Model	Data	Model	Data	Model
1	0.009	0.004	0.008	0.005	0.010	0.007	0.009	0.006
2	0.013	0.012	0.013	0.014	0.015	0.019	0.015	0.017
3	0.017	0.018	0.016	0.021	0.019	0.028	0.019	0.026
4	0.022	0.024	0.021	0.028	0.024	0.037	0.024	0.033
5	0.029	0.030	0.028	0.034	0.034	0.046	0.033	0.041
6	0.038	0.037	0.036	0.041	0.043	0.055	0.042	0.050
7	0.052	0.050	0.050	0.054	0.058	0.069	0.057	0.065
8	0.074	0.081	0.071	0.085	0.083	0.103	0.081	0.100
9	0.124	0.153	0.119	0.157	0.136	0.175	0.135	0.173
10	0.622	0.590	0.636	0.561	0.578	0.461	0.584	0.488

Notes: Each column of the table shows the share of the location's workers employed at firms in the decile of the location's firm size distribution indicated in column 1. The empirical moments are computed as described in Supplemental Appendix Q.2.9.

Table S65: Share of Workers by Firm Size Decile and Location – All Moves

	NW		SW		NE		SE	
Decile	Data	Model	Data	Model	Data	Model	Data	Model
1	0.009	0.004	0.008	0.005	0.010	0.006	0.009	0.006
2	0.013	0.010	0.013	0.012	0.015	0.017	0.015	0.015
3	0.017	0.015	0.016	0.017	0.019	0.024	0.019	0.022
4	0.022	0.019	0.021	0.022	0.024	0.030	0.024	0.028
5	0.029	0.023	0.028	0.026	0.034	0.037	0.033	0.033
6	0.038	0.029	0.036	0.031	0.043	0.045	0.042	0.041
7	0.052	0.042	0.050	0.045	0.058	0.063	0.057	0.060
8	0.074	0.068	0.071	0.072	0.083	0.098	0.081	0.094
9	0.124	0.133	0.119	0.138	0.136	0.172	0.135	0.168
10	0.622	0.657	0.636	0.632	0.578	0.507	0.584	0.534

Notes: Each column of the table shows the share of the location's workers employed at firms in the decile of the location's firm size distribution indicated in column 1. The empirical moments are computed as described in Supplemental Appendix Q.2.9.

U.10 Relationship between Firm Wage and Firm Size

Table S66: Log Wage on Log Firm Size by Location – Benchmark

Location	Data	Model
NW	0.124	0.126
SW	0.124	0.161
NE	0.110	0.135
SE	0.109	0.140

Notes: The table presents the coefficients from a regression of log firm wage on log firm size, where the empirical moments are constructed as described in Supplemental Appendix Q.2.10.

Table S67: Log Wage on Log Firm Size by Location – Only Migration Moves

Location	Data	Model
NW	0.124	0.128
SW	0.124	0.173
NE	0.110	0.139
SE	0.109	0.146

Notes: The table presents the coefficients from a regression of log firm wage on log firm size, where the empirical moments are constructed as described in Supplemental Appendix Q.2.10.

Table S68: Log Wage on Log Firm Size by Location – All Moves

Location	Data	Model
NW	0.124	0.134
SW	0.124	0.167
NE	0.110	0.146
SE	0.109	0.149

Notes: The table presents the coefficients from a regression of log firm wage on log firm size, where the empirical moments are constructed as described in Supplemental Appendix Q.2.10.

U.11 Wage Gains of Job-to-Job Movers by Origin Firm Wage

Table S69: Log Wage Gain of Movers by Initial Wage – Benchmark

Location	Data	Model
NW	-0.549	-0.805
SW	-0.577	-0.827
NE	-0.562	-0.889
SE	-0.561	-0.870

Notes: The table presents the coefficients from a regression of the log average wage gain of job-to-job movers on the log average wage of the firm of origin, where the empirical moments are constructed as described in Supplemental Appendix Q.2.11.

Table S70: Log Wage Gain of Movers by Initial Wage – Migration Moves

Location	Data	Model
NW	-0.549	-0.832
SW	-0.577	-0.851
NE	-0.562	-0.910
SE	-0.561	-0.893

Notes: The table presents the coefficients from a regression of the log average wage gain of job-to-job movers on the log average wage of the firm of origin, where the empirical moments are constructed as described in Supplemental Appendix Q.2.11.

Table S71: Log Wage Gain of Movers by Initial Wage – All Moves

Location	Data	Model
NW	-0.549	-0.739
SW	-0.577	-0.759
NE	-0.562	-0.838
SE	-0.561	-0.821

Notes: The table presents the coefficients from a regression of the log average wage gain of job-to-job movers on the log average wage of the firm of origin, where the empirical moments are constructed as described in Supplemental Appendix Q.2.11.

U.12 Separation Rate by Initial Wage

Table S72: Avg. Separation Rates of Workers by Initial Wage – Benchmark

Location	Data	Model
NW	-0.029	-0.024
SW	-0.033	-0.024
NE	-0.037	-0.019
SE	-0.036	-0.020

Notes: The table presents the coefficients from a regression of a dummy for separations to another job, unemployment, or permanent non-employment on the log average wage of the firm of origin, where the empirical moments are constructed as described in Supplemental Appendix Q.2.12.

Table S73: Avg. Separation Rates of Workers by Initial Wage – Only Migration Moves

Location	Data	Model
NW	-0.029	-0.018
SW	-0.033	-0.018
NE	-0.037	-0.015
SE	-0.036	-0.015

Notes: The table presents the coefficients from a regression of a dummy for separations to another job, unemployment, or permanent non-employment on the log average wage of the firm of origin, where the empirical moments are constructed as described in Supplemental Appendix Q.2.12.

Table S74: Avg. Separation Rates of Workers by Initial Wage – All Moves

Location	Data	Model
NW	-0.029	-0.032
SW	-0.033	-0.032
NE	-0.037	-0.024
SE	-0.036	-0.025

Notes: The table presents the coefficients from a regression of a dummy for separations to another job, unemployment, or permanent non-employment on the log average wage of the firm of origin, where the empirical moments are constructed as described in Supplemental Appendix Q.2.12.

U.13 Standard Deviation of Wage Gains

Table S75: Standard Deviation of the Residual Wage Gains for Job Movers – Benchmark

Move to Location:		NW		SW		NE		SE	
Birth Location	Work Location	Data	Model	Data	Model	Data	Model	Data	Model
NW	NW	0.564	0.386	0.763	0.393	0.640	0.377	0.772	0.375
	SW	0.656	0.402	0.546	0.412	0.655	0.391	0.546	0.389
	NE	0.545	0.392	0.671	0.389	0.442	0.368	0.486	0.368
	SE	0.562	0.389	0.435	0.391	0.589	0.369	0.435	0.371
SW	NW	0.558	0.395	0.660	0.400	0.652	0.385	0.644	0.383
	SW	0.743	0.389	0.543	0.404	0.948	0.383	0.734	0.382
	NE	0.834	0.385	0.682	0.396	0.413	0.368	0.463	0.369
	SE	0.625	0.382	0.589	0.395	0.392	0.369	0.437	0.372
NE	NW	0.445	0.403	0.587	0.409	0.522	0.385	0.584	0.387
	SW	0.573	0.407	0.457	0.419	0.473	0.392	0.520	0.394
	NE	0.651	0.375	0.752	0.384	0.455	0.362	0.684	0.361
	SE	0.695	0.384	0.503	0.393	0.525	0.368	0.472	0.372
SE	NW	0.477	0.405	0.613	0.412	0.485	0.390	0.499	0.387
	SW	0.661	0.409	0.470	0.421	0.691	0.396	0.530	0.396
	NE	0.640	0.385	0.628	0.393	0.424	0.370	0.578	0.371
	SE	0.729	0.378	0.645	0.389	0.526	0.365	0.471	0.366

Notes: The table shows the standard deviation of the wage gains of job-to-job movers for workers of a given home location (column 1) and current work location (column 2) that move jobs to a given destination location (top row). The empirical moments are constructed as described in Supplemental Appendix Q.2.13.

Table S76: Standard Deviation of the Residual Wage Gains for Job Movers – Only Migration Moves

Move to Location:		NW		SW		NE		SE	
Birth Location	Work Location	Data	Model	Data	Model	Data	Model	Data	Model
NW	NW	0.564	0.432	0.818	0.440	0.694	0.422	0.815	0.421
	SW	0.669	0.447	0.546	0.460	0.662	0.436	0.583	0.436
	NE	0.605	0.430	0.670	0.431	0.442	0.408	0.633	0.407
	SE	0.594	0.429	0.468	0.434	0.521	0.411	0.435	0.414
SW	NW	0.558	0.444	0.673	0.447	0.686	0.430	0.674	0.430
	SW	0.821	0.434	0.543	0.451	0.968	0.428	0.864	0.428
	NE	0.944	0.423	0.697	0.437	0.413	0.408	0.440	0.408
	SE	0.694	0.424	0.634	0.437	0.425	0.411	0.437	0.415
NE	NW	0.445	0.451	0.562	0.458	0.522	0.429	0.631	0.434
	SW	0.592	0.454	0.457	0.468	0.474	0.437	0.534	0.440
	NE	0.784	0.415	0.765	0.427	0.455	0.401	1.011	0.401
	SE	0.737	0.427	0.550	0.438	0.596	0.408	0.472	0.415
SE	NW	0.477	0.453	0.633	0.460	0.482	0.435	0.503	0.432
	SW	0.671	0.456	0.470	0.469	0.691	0.441	0.546	0.441
	NE	0.704	0.426	0.678	0.436	0.424	0.409	0.689	0.411
	SE	0.779	0.420	0.769	0.433	0.670	0.406	0.471	0.408

Notes: The table shows the standard deviation of the wage gains of job-to-job movers for workers of a given home location (column 1) and current work location (column 2) that move jobs to a given destination location (top row). The empirical moments are constructed as described in Supplemental Appendix Q.2.13.

Table S77: Standard Deviation of the Residual Wage Gains for Job Movers – All Moves

Move to Location:		NW		SW		NE		SE	
Birth Location	Work Location	Data	Model	Data	Model	Data	Model	Data	Model
NW	NW	0.564	0.387	0.697	0.404	0.576	0.385	0.678	0.386
	SW	0.596	0.409	0.546	0.425	0.613	0.405	0.486	0.405
	NE	0.529	0.404	0.546	0.408	0.442	0.383	0.479	0.385
	SE	0.562	0.402	0.536	0.409	0.541	0.384	0.435	0.386
SW	NW	0.557	0.414	0.555	0.409	0.499	0.402	0.591	0.402
	SW	0.688	0.404	0.543	0.401	0.749	0.391	0.621	0.392
	NE	0.653	0.407	0.675	0.408	0.413	0.383	0.411	0.387
	SE	0.548	0.405	0.529	0.407	0.484	0.384	0.437	0.387
NE	NW	0.445	0.416	0.510	0.419	0.515	0.390	0.577	0.398
	SW	0.549	0.420	0.457	0.426	0.514	0.395	0.517	0.403
	NE	0.591	0.391	0.632	0.395	0.455	0.363	0.643	0.370
	SE	0.624	0.401	0.490	0.405	0.493	0.373	0.472	0.381
SE	NW	0.477	0.419	0.511	0.424	0.459	0.401	0.530	0.393
	SW	0.562	0.423	0.470	0.431	0.563	0.405	0.509	0.399
	NE	0.514	0.405	0.509	0.408	0.424	0.380	0.519	0.378
	SE	0.634	0.392	0.609	0.398	0.507	0.371	0.471	0.365

Notes: The table shows the standard deviation of the wage gains of job-to-job movers for workers of a given home location (column 1) and current work location (column 2) that move jobs to a given destination location (top row). The empirical moments are constructed as described in Supplemental Appendix Q.2.13.

U.14 Profit Shares of Labor Costs

Table S78: Average Ratio of Firm Profits to Labor Costs by Location – Benchmark

	Average Profit Share	
Location	Data	Model
NW	0.274	0.285
SW	0.259	0.303
NE	0.299	0.360
SE	0.263	0.342

Notes: The table presents the average ratio of firm profits to total labor costs for firms in the location indicated in the first column. The empirical moments are constructed as described in Supplemental Appendix Q.2.14.

Table S79: Average Ratio of Firm Profits to Labor Costs by Location – Only Migration Moves

	Average Profit Share	
Location	Data	Model
NW	0.274	0.325
SW	0.259	0.345
NE	0.299	0.407
SE	0.263	0.387

Notes: The table presents the average ratio of firm profits to total labor costs for firms in the location indicated in the first column. The empirical moments are constructed as described in Supplemental Appendix Q.2.14.

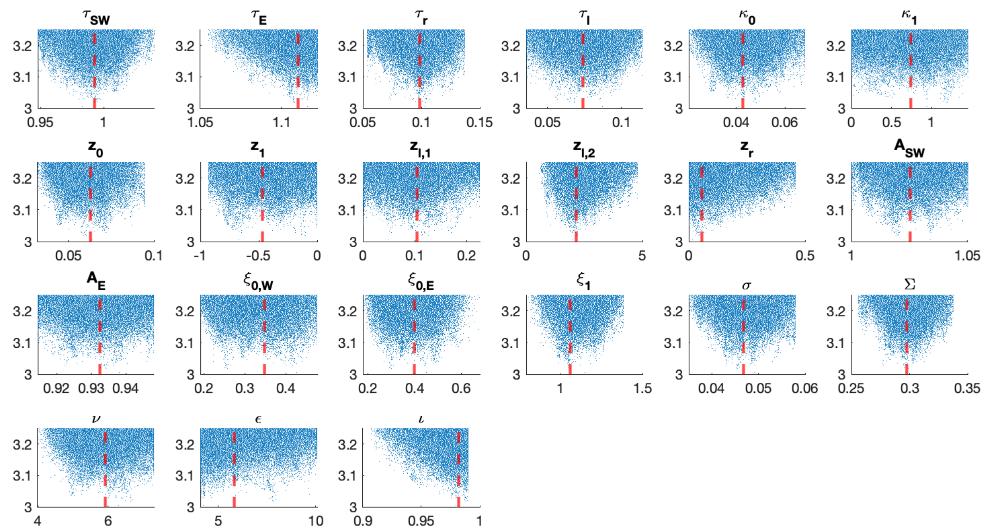
Table S80: Average Ratio of Firm Profits to Labor Costs by Location – All Moves

	Average Profit Share	
Location	Data	Model
NW	0.274	0.251
SW	0.259	0.265
NE	0.299	0.328
SE	0.263	0.313

Notes: The table presents the average ratio of firm profits to total labor costs for firms in the location indicated in the first column. The empirical moments are constructed as described in Supplemental Appendix Q.2.14.

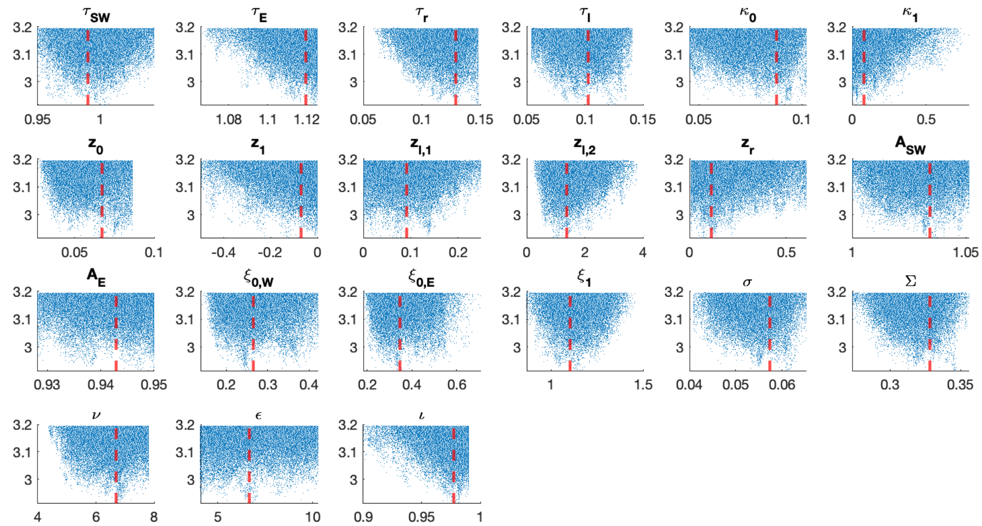
U.15 Likelihood Functions around Estimated Parameters

Figure S21: Likelihood Plots; Benchmark



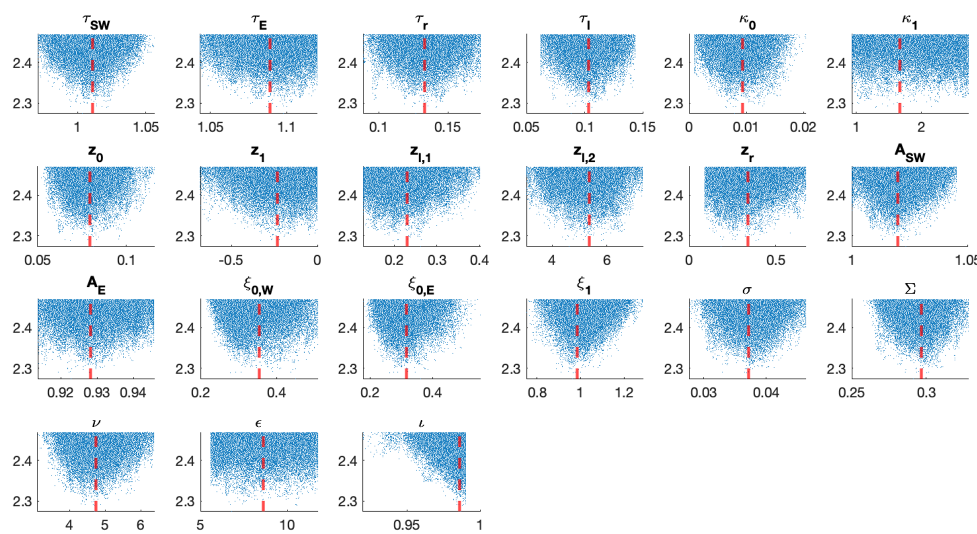
Notes: The table presents on the y-axis the draws of the best 10,000 values of the likelihood functions along the final estimation chain. On the x-axis, values of each one of the 21 primitive parameters are reported. We highlight with a red dotted line the estimated values for each parameter. If the model is locally tightly identified, we would expect the likelihood to be single peaked with the minimum at the estimated parameter values. This figure builds confidence that our model is, in fact, quite well-identified, especially for the key parameter modulating the spatial frictions.

Figure S22: Likelihood Plots; Only Migration Moves



Notes: The table presents on the y-axis the draws of the best 10,000 values of the likelihood functions along the final estimation chain, for the “Only Migration Moves” estimation. On the x-axis, values of each one of the 21 primitive parameters are reported. We highlight with a red dotted line the estimated values for each parameter. If the model is locally tightly identified, we would expect the likelihood to be single peaked with the minimum at the estimated parameter values. This figure builds confidence that our model is, in fact, quite well-identified, especially for the key parameter modulating the spatial frictions.

Figure S23: Likelihood Plots; All Moves



Notes: The table presents on the y-axis the draws of the best 10,000 values of the likelihood functions along the final estimation chain, for the “All Moves” estimation. On the x-axis, values of each one of the 21 primitive parameters are reported. We highlight with a red dotted line the estimated values for each parameter. If the model is locally tightly identified, we would expect the likelihood to be single peaked with the minimum at the estimated parameter values. This figure builds confidence that our model is, in fact, quite well-identified, especially for the key parameter modulating the spatial frictions.

V The Importance of Family Ties

In this section, we further explore one potential source of home preferences. We exploit the fact that the German Socioeconomic Panel (SOEP) records when individuals have a child to examine the role of a child birth on workers' mobility. We perform this analysis on the "Old SOEP Sample". As described in the SOEP Appendix C, this sample consists of individuals first in the SOEP in 1984, which covered only West German individuals, and individuals in the SOEP first drawn in a wave in 1990, which covered only East German individuals.[77] The birth region of these individuals is thus known with certainty. For individuals drawn from these waves, we consider the sub-sample of full-time workers that are employed at time t in their non-native region and run, for the period from 1993-2016,

$$Migr_{it} = \alpha + \sum_{\tau=-3}^{3} \beta_\tau \mathbb{D}_\tau + \epsilon_{it}, \tag{69}$$

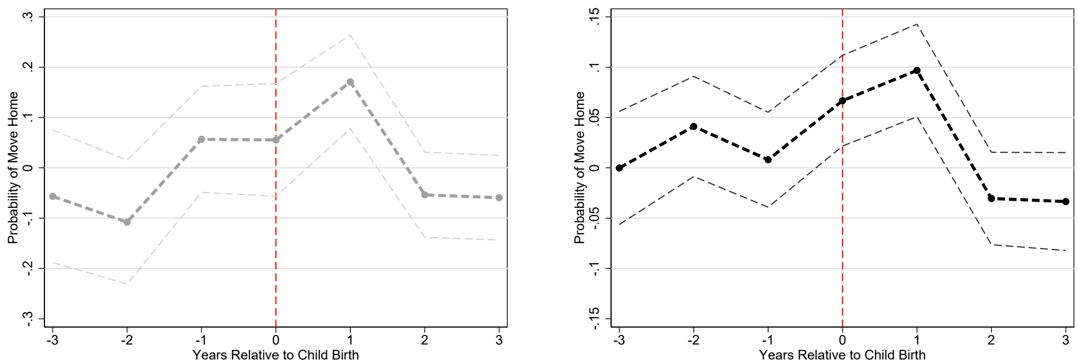
where $Migr_{it}$ is a dummy that is equal to one if worker i moves back to her home region at time t, and $\mathbb{D}_\tau$ are dummies around a child birth event (at $\tau = 0$). Figure S24a shows the estimated coefficients for East-to-West return moves of West-born workers, while Figure S24b presents the coefficients for West-to-East return moves of East-born workers.

We find a significant spike of return moves one year after the birth of a child, thus suggesting that young parents might be more willing to move back home, possibly to benefit from childcare support from their own parents. The finding suggests that familial ties may be important in explaining workers' attachment to their home region.

[77] The "New SOEP Sample" only has an extremely small number of child births, which does not allow us to run this regression in that sample.

Figure S24: Child Birth Event Study

(a) West to East Return Move Probability (b) East to West Return Move Probability



Source: SOEP and authors' calculations. Notes: We plot the point estimates from specification (69). The left panel shows the probability, around the event of the birth of a child, that an East-born worker that has previously migrated to the West returns back to the East. The right panel shows the same for a West-born worker. The dotted lines represent the 95% confidence intervals. We notice that both East- and West-born individuals are more likely to return back to their birth region right after the birth of a child.

W Additional Quantitative Results

We here present some additional results from the quantitative exercises of Section 6.

Table S81 presents the full counterfactual results underlying Figure 6. We additionally include in the table the change in the nominal wage, $w_j(p)\,\theta^i_j$, and the change in the unemployment rate. Moreover, we include the wage rate per efficiency unit, $w_j(p)$, to highlight the difference with the average wage, which depends on the composition of workers (θ^i_j) in each region.

Figure S25 presents the same statistics as in Figure 6, split by location. The results are similar for the locations within the same region, and hence we present the results by region in the main text.

Figure S26 presents posted vacancies, workers' acceptance probability, and the separation rate as a function of firm productivity as in Figure 8, but for West Germany. The findings are similar to the figure shown in the main text: the number of vacancies and the separation rate contribute positively to the reallocation of labor from low- to high-productivity firms, while the acceptance probability mitigates the reallocation gains.

Figure S27 shows the distribution of workers to firms, analogously to Figure 7, for the partial equilibrium counterfactual where we hold fixed firms' wage and vacancy posting. Consistent with the relatively small aggregate effects, we see little change in the overall worker distribution (Panel (a)). However, there is reallocation across regions as East Germans move West and West Germans move East, as illustrated in Panels (b) and (c).

Figures S28 and S29 show the distribution of workers to firms, analogously to Figure 7, for the counterfactuals where only technological spatial frictions are removed or where only preference frictions are removed. Removing only technological spatial frictions generates some improvement in the worker allocation both within and across regions. In contrast, removing preference frictions mostly changes the allocation of workers across regions.

Finally, Figure S30 presents some additional plots showing the effects of removing spatial frictions on within-location wage gains, total value (welfare), and the relative wage increase of East Germans as we vary labor market frictions as in Figure 9. Panel (a) shows that the within-location wage gains for movers decline sharply with the variance of preference shocks σ, but are relatively unaffected by the other two parameters.[78] When σ is large, workers' moves are more frequently due to preferences rather than wage differences, reducing the average wage gain. The impact of the spatial frictions on either the workers' value or the relative wage of East Germans is much less sensitive to the value of the labor market

[78] We note that the changes in cross-location flows and wage gains are very similar (in percentage terms).

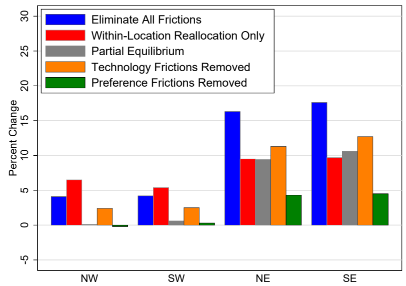
parameters (Panels (b) and (c)). For these two statistics, the allocation of labor within location is less relevant: removing spatial frictions mostly changes the value functions because workers receive more job opportunities and no longer pay the moving or utility cost, rather than because of within-location frictions. Similarly, East Germans' wages rise relative to West Germans' mainly because they move to the higher productivity West.

Table S81: Model Counterfactuals with Reduced Spatial Frictions

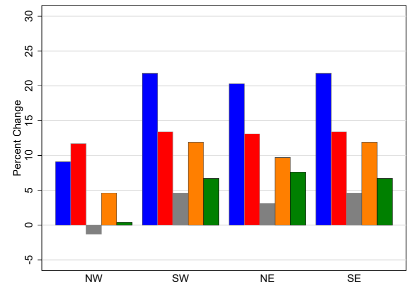
			All Frictions	w/i Locations	Partial Eq.	Technology	Preferences
			(1)	(2)	(3)	(4)	(5)
Panel (a): Aggregate							
Overall	(1)	Output pc	+ 4.7 %	+ 6.6 %	+ 0.5 %	+ 2.7 %	+ 0.7 %
	(2)	Value Function	+ 37.0 %	+ 37.1 %	+ 22.0 %	+ 25.1 %	+ 2.9 %
	(3)	Wage	+ 9.1 %	+ 11.3 %	- 2.1 %	+ 3.8 %	+ 1.7 %
	(4)	Real Wage	+ 9.6 %	+ 11.3 %	- 1.6%	+ 4.2 %	+ 1.8 %
	(5)	Unemployment	- 2.3 pp	- 0.2 pp	- 1.9 pp	- 2.2 pp	- 0.1 pp
	(6)	% Workers in West	- 10.9 pp	/	- 8.7 pp	- 8.2 pp	- 0.6 pp
Panel (b): By region							
West	(7)	Output pc	+ 4.2 %	+ 6.0 %	+ 0.4 %	+ 2.5 %	+ 0.1 %
	(8)	Value Function	+ 33.3 %	+ 35.0 %	+ 18.8 %	+ 22.1 %	+ 1.8 %
	(9)	Wage	+ 8.6 %	+ 10.5 %	- 1.5 %	+ 4.1 %	+ 0.8 %
	(10)	Real Wage	+ 9.2 %	+ 11.1 %	- 0.9 %	+ 4.6 %	+ 0.9 %
	(11)	Wage per eff. unit	+ 10.2 %	+ 10.5 %	+ 0.4 %	+ 5.6 %	+ 1.4 %
	(12)	Unemployment	- 2.2 pp	- 0.2 pp	- 1.7 pp	- 2.1 pp	- 0.1 pp
East	(13)	Output pc	+ 17.0 %	+ 9.6 %	+ 10.0 %	+ 12 %	+ 4.5 %
	(14)	Value Function	+ 53.7 %	+ 46.2 %	+ 36.6 %	+ 39.1 %	+ 8.1 %
	(15)	Wage	+ 24.6 %	+ 16.6 %	+ 6.2 %	+ 13.3 %	+ 7.6 %
	(16)	Real Wage	+ 21.1 %	+ 13.3 %	+ 3.8 %	+ 10.8 %	+ 7.2 %
	(17)	Wage per eff. unit	+ 17.4 %	+ 16.6 %	+ 0.4 %	+ 7.1 %	+ 5.0 %
	(18)	Unemployment	- 4.1 pp	- 0.2 pp	- 3.8 pp	- 3.8 pp	- 0.2 pp
Panel (c): By worker type							
Born West	(19)	Output pc	+ 1.9 %	+ 6.0 %	- 2.1 %	+ 0.3 %	- 0.4 %
	(20)	Value Function	+ 34.3 %	+ 34.5 %	+ 19.8 %	+ 23.2 %	+ 1.9 %
	(21)	Wage	+ 6.0 %	+ 10.6 %	- 5.0 %	+ 1.3 %	+ 0.3 %
	(22)	Real Wage	+ 7.5 %	+ 11.1 %	- 3.6 %	+ 2.6 %	+ 0.8 %
	(23)	Unemployment	- 1.6 pp	+ 0.2 pp	- 1.1 pp	- 1.5 pp	+ 0.2 pp
	(24)	% Workers in West	- 27.3 pp	/	- 25.1 pp	- 23.2 pp	- 6.8 pp
Born East	(25)	Output pc	+ 15.9 %	+ 8.7 %	+ 11.3 %	+ 12.1 %	+ 5.1 %
	(26)	Value Function	+ 47.2 %	+ 47.0 %	+ 30.5 %	+ 32.1 %	+ 6.6 %
	(27)	Wage	+ 23.1 %	+ 14.8 %	+ 10.4 %	+ 15 %	+ 8 %
	(28)	Real Wage	+ 18.9 %	+ 12.7 %	+ 6.7 %	+ 11.2 %	+ 6.2 %
	(29)	Unemployment	- 4.8 pp	- 1.3 pp	- 4.3 pp	- 4.5 pp	- 1.0 pp
	(30)	% Workers in West	+ 43.5 pp	/	+ 45.6 pp	+ 41.4 pp	+ 20.6 pp

Figure S25: Aggregate and Distributional Effects of Removing Spatial Frictions, by Location

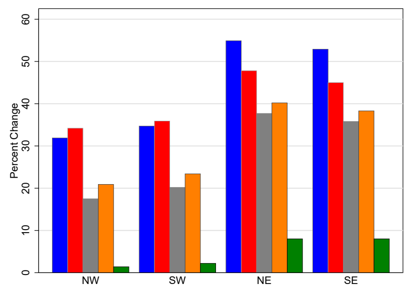
(a) Change in Output per Capita



(b) Change in Real Wage



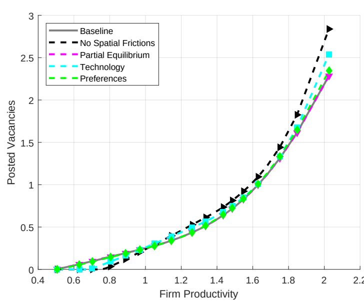
(c) Change in Value Function



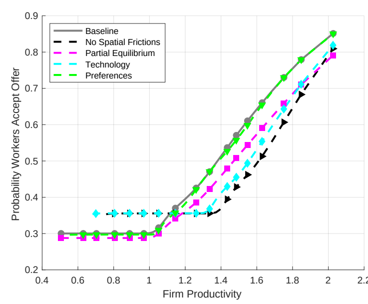
Notes: Figure shows the effects of various exercises, shown with the different-colored bars, on three outcomes: output per worker (top-left), real wage (top-right), and average value (bottom). Bars show percentage change relative to the baseline economy.

Figure S26: Margins of Employment, West Germany

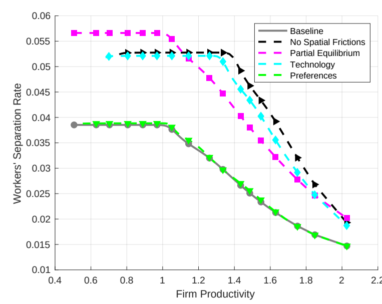
(a) Posted Vacancies



(b) Acceptance Probability



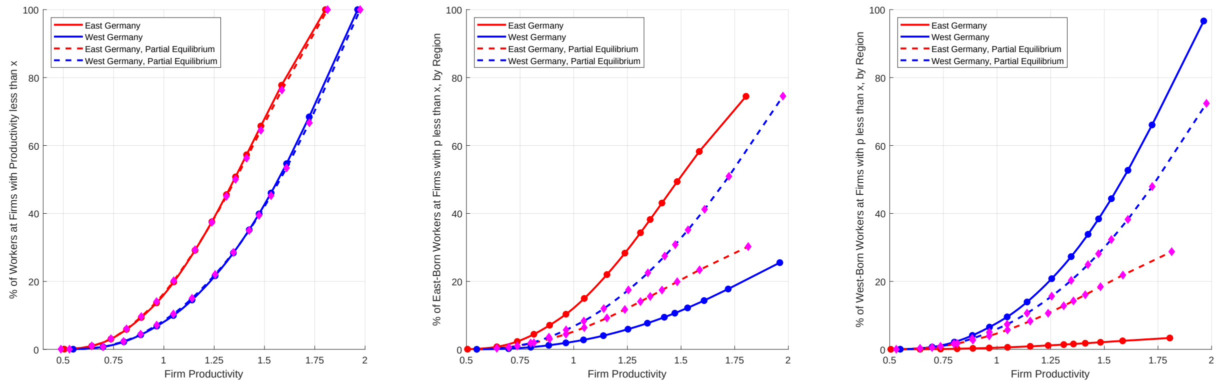
(c) Separation Rate



Notes: All panels are for firms in West Germany and show outcomes as a function of firm productivity. The left panel shows the change in the number of posted vacancies. The middle panel shows the probability that a given wage is accepted by the worker it matches with. The right panel shows the monthly rate at which workers separate towards either other firms or unemployment. We consider four possible counterfactuals, described in text.

Figure S27: Labor Allocation Across Firms and Regions, Partial Equilibrium

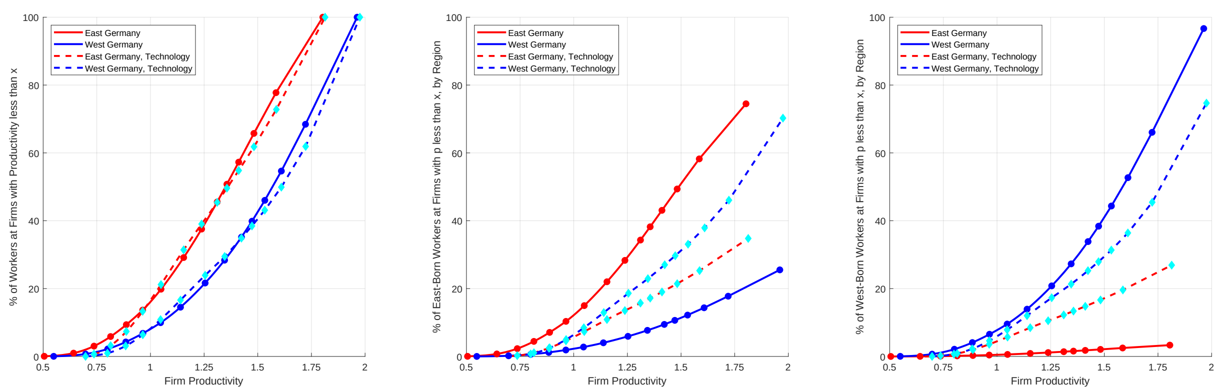
(a) All Workers (b) East Germans (c) West Germans



Notes: The left panel shows the CDF of workers over firm productivity within East (in red) and West Germany (in blue). The solid line is our benchmark estimation, while the dashed one the counterfactual without spatial frictions when we keep constant the firm equilibrium response. The middle panel is a semi-CDF that shows the distribution of employment for East German workers across the whole Germany. To interpret the figure, consider that, at baseline, more than 75% of employment is in East Germany, and the remaining employment is in the West (i.e., the two last points of the solid lines add up to one, and similar for the dashed lines). The right panel shows the same semi-CDF for West Germans.

Figure S28: Labor Allocation Across Firms and Regions, Technology

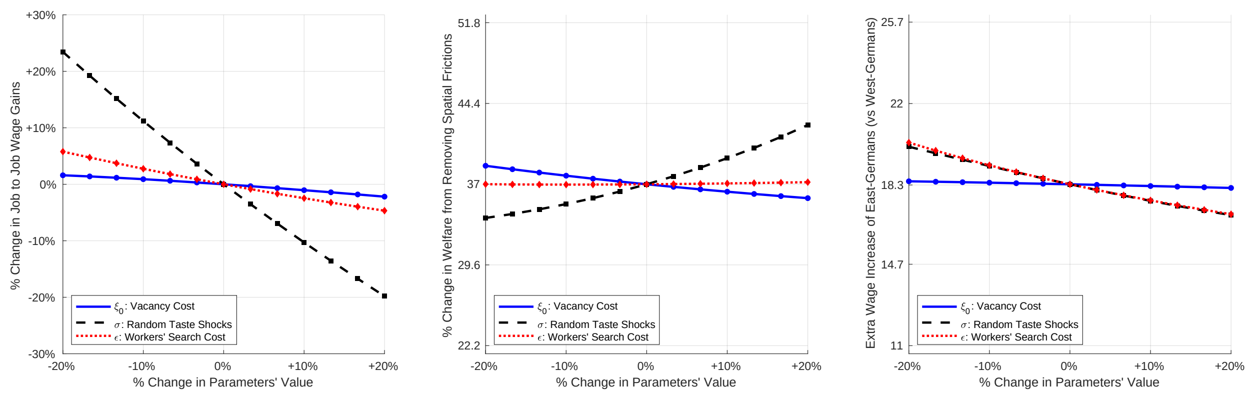
(a) All Workers (b) East Germans (c) West Germans



Notes: The left panel shows the CDF of workers over firm productivity within East (in red) and West Germany (in blue). The solid line is our benchmark estimation, while the dashed one the counterfactual in which we eliminate spatial frictions due to technology (i.e. z and κ). The middle panel is a semi-CDF that shows the distribution of employment for East German workers across the whole Germany. To interpret the figure, consider that, at baseline, more than 75% of employment is in East Germany, and the remaining employment is in the West (i.e., the two last points of the solid lines add up to one, and similar for the dashed lines). The right panel shows the same semi-CDF for West Germans.

Figure S30: Additional Plots on the Sensitivity of Micro and Macro Moments to Labor Market Parameters

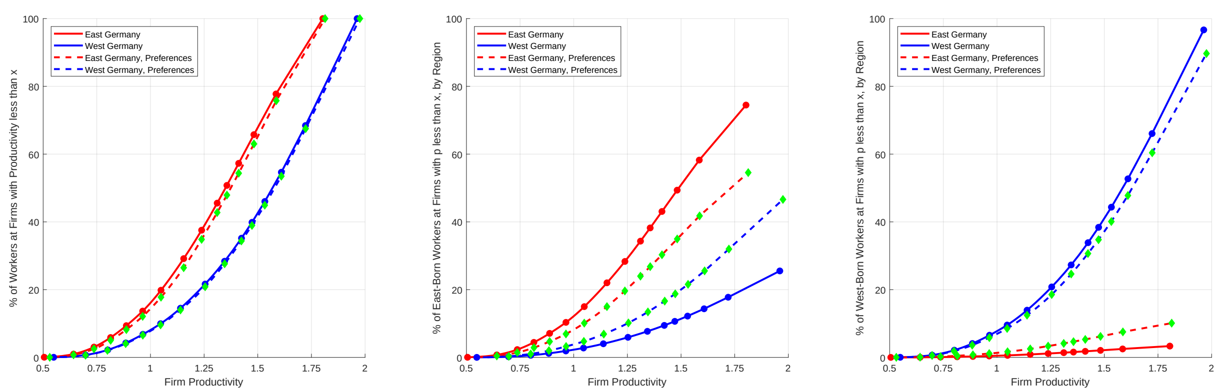
(a) Within-Location Wage Gains (b) Welfare Gains (c) Wage Gains of East Germans



Notes: We vary three labor market parameters and recompute the effect of removing spatial frictions under these alternative calibrations. The left panel shows the change in the wage gains obtained from moves within region relative to the baseline. The middle panel shows the change in workers' value function. The right panel presents the relative wage increase of East-born.

Figure S29: Labor Allocation Across Firms and Regions, Preferences

(a) All Workers (b) East Germans (c) West Germans



Notes: The left panel shows the CDF of workers over firm productivity within East (in red) and West Germany (in blue). The solid line is our benchmark estimation, while the dashed one the counterfactual in which we eliminate spatial frictions due to preferences (i.e. τ). The middle panel is a semi-CDF that shows the distribution of employment for East German workers across the whole Germany. To interpret the figure, consider that, at baseline, more than 75% of employment is in East Germany, and the remaining employment is in the West (i.e., the two last points of the solid lines add up to one, and similar for the dashed lines). The right panel shows the same semi-CDF for West Germans.

X Additional Information on the SCE

X.1 Data Preparation

We use the yearly job search supplement from the NY Fed's Survey of Consumer Expectations (SCE) for the years 2013-2020. In contrast to the overall SCE, the job search survey is not a panel, but rather a series of cross-sectional surveys with differing participants. We obtain from the survey workers' wage in their current job (reported as an annual, weekly, or hourly wage; from question L11: "How much do you make before taxes or other deductions at your main/current job? Please include any bonuses, overtime pay, tips, or commissions"), commuting time to the job (EC5: "What is the average time you spend commuting from your main/current job each day"), workers' location at the ZIP code level, the reservation wage (RW2: "Suppose someone offered you a job today. What is the lowest wage or salary you would accept (before taxes and deductions) for the type of work you are looking for?"), time spent searching for a new job in the past seven days (JS7: "And within the last 7 days, about how many total hours did you spend on job search activities?"), and number of job applications sent in the past four weeks (JS14: "How many potential employers, if any, did you apply to for employment in the last four weeks? Please include all applications made in person, online, or through other direct methods. Do not include inquiries that did not lead to a job application.").

We focus on workers that are employed, and drop the self-employed. We translate hourly wages into a weekly wage using respondents' hours worked. We cap the number of hours worked at 90 for outliers that report a greater number of hours. As we do not observe the number of weeks worked, we divide the annual wage by 52 weeks to calculate the weekly rate. We perform similar steps for the reservation wage. To capture outliers, we replace weekly wages exceeding 5,770 dollars (300,000 annually) with this maximum value. Similarly, we cap the commuting time at a maximum of 4 hours per roundtrip, the time spent searching for a job at 70 hours per week, and the number of applications sent in the past four weeks at 100. We create three age brackets using respondents' demographic information: young (less than 25 years old), middle (25-54 years), and older (above 54 years). Furthermore, we generate a dummy for high education (bachelor's degree and above). We also obtain each workers' industry code. The SCE distinguishes 20 broad industries, which correspond to 2-digit NAICS codes with the exception of NAICS codes 54-56, which are grouped together.

We combine the individual-level SCE data with two datasets. First, we construct the local wage distribution from the American Community Survey (ACS), using the 5-year sample from 2015-2019 obtained from IPUMS. Second, we obtain indicators for the local labor market "density" from the Census Bureau's County Business Patterns (CBP) for 2013-2020.[79]

Our ACS sample provides us with information for about 16 million individuals. We drop anyone who has missing labor market data (such as children), anyone who is unemployed, and anyone who is self-employed. Since the ACS does not have a specific question about part-time work, we treat anyone who works at least 30 hours as a full-time worker, and drop all remaining observations. The remaining dataset has about 5.6 million observations. We then create weekly wages from each respondent's yearly wage income. In 2019, we observe individuals' number of weeks worked in the year and divide yearly wage income by this variable. In 2015-2018, we do not have information on the number of weeks worked. We therefore assume that individuals worked the entire year and divide yearly wage by 52. For reference, 89% of full-time employees in 2019 that report weeks reported that they worked 52 weeks. We map industries to the industry codes in the SCE. We then map each individual's Public Use Microdata Area (PUMA) to commuting zones using the crosswalk by David Dorn.[80] Finally, we compute the 25th, 50th, and 75th percentile of weekly wages for each industry and commuting zone, where we aggregate across individuals using individual weights from the ACS multiplied by the PUMA population shares in each commuting zone from David Dorn.

The CBP data provide the number of workers and establishments within a given industry and county in each year. We code the number of workers as missing for counties that have a high noise flag, and combine 6-digit NAICS industries to the same broad industries as in the SCE. We then aggregate the data to the commuting zone level in two steps. First, we map each county to its PUMA using a mapping provided by the Census Bureau. For counties that contain several PUMAs, we split up the employment and number of establishments in each industry using population weights from the ACS data. Each PUMA-by-industry cell is associated with the county's share of employment and establishments in the industry proportional to the PUMA-by-industry's number of full-time wage and salary workers from the ACS. If the PUMA is associated with several counties we sum across counties. In the second step, we map PUMAs to commuting zones using the crosswalk by David Dorn as before. Our final CBP dataset thus contains the total employment and number of establishments by industry and commuting zone.

We finally map each worker in the SCE to the associated wage distribution, employment, and number of establishments for the commuting zone associated with the worker's ZIP code. We obtain a mapping between ZIP codes and counties from the U.S. Department of Housing

[79]Obtained from https://www.census.gov/programs-surveys/cbp/data/datasets.html

[80]Obtained from https://www.ddorn.net/data.htm

and Urban Development.[81] Since ZIP codes are subject to change, HUD offers crosswalks at quarterly frequency. We use the mapping from ZIP codes to counties in the 4th Quarter of every year. We then map the counties to PUMAs using the Census Bureau's crosswalk, and use David Dorn's crosswalk to map to commuting zones. Thus, we obtain a link between respondents' ZIP codes and their commuting zone wage distribution, employment, and establishments. For ZIP codes that are associated with multiple commuting zones, we take a weighted average using commuting zone level employment as constructed above as weight. Our final dataset contains for each worker the wage distribution, employment, and the number of establishments in the associated commuting zone.

X.2 Results

We provide the main regression results in Appendix I, and provide here some additional results.

We first provide some summary statistics on workers' willingness to relocate (from question RW3: "[All who looked for new/additional work in the last 4 weeks, or want or might want a new/additional job]. Suppose you were offered a job today that paid your reservation wage. Would you accept this job if it required you to relocate to another city or state?"). We find that only about 25% of workers looking for jobs would accept a position in another city or state at their reservation wage, suggesting some location preference or moving costs. The results are similar for currently employed and unemployed workers. From workers' required wage increase to relocate (RW3b: "By what percentage would the wage have to be higher, if at all, for you to relocate?"), we find that about 50% of job seekers would not move to another city or state for *any* wage increase. Finally, we compute the wage increase required by job seekers to accept a job that doubles their commuting time (RW4b: "By what percentage would the wage have to be higher, if at all, for you to double your daily commute?"), focusing on individuals that would be willing to take such a commute at all. We find that workers in the U.S. require a median wage increase of 30% to double their commute.

We next present alternative regressions where we use job satisfaction instead of commuting time as right-hand side variable (question EC13: "Taking everything into consideration, how satisfied would you say you are, overall, in your [current/main] job?"). Similar to the main appendix, we run regressions of the form

$$y_i = \sum_k \beta_k \mathbb{I}(\text{Satisfaction}_i = k) + \alpha X_i + \epsilon_{ins},$$

[81] https://www.huduser.gov/portal/datasets/usps_crosswalk.html

where y_i is the inverse hyperbolic sine (IHS) transformation of employed worker i's number of applications sent to employers in the last four weeks or the number of hours spent searching for jobs in the last seven days. We use the IHS since many workers report zeros. The variables $\mathbb{I}(\text{Satisfaction}_i = k)$ are four dimmies for $k = 2$: "Somewhat dissatisfied", $k = 3$: "Neither satisfied nor dissatisfied", $k = 4$: "Somewhat satisfied", and $k = 5$: "Very satisfied" (with the omitted category being "Very dissatisfied"). The term X_i contains controls for gender, age dummies, a dummy for a college degree, industry fixed effects, and state fixed effects. The first two columns of Table S82 show the results for applications and search hours. We find that greater job satisfaction is negatively related to search effort, consistent with better-matched workers exerting less search effort.

We next run our baseline regressions from Appendix I, where instead of applications we use the IHS of the number of hours spent on searching for jobs in the last 7 days as the left-hand side variable. Specifically, we run

$$y_i = \beta_1 \ln(wage_i) + \beta_2 \ln(comm_i) + \sum_{k=2}^{4} \delta_k wage_i(Q_k) + \alpha X_i + \epsilon_{ins},$$

where y_i is the IHS of number of hours searched, $wage_i$ is the worker's weekly wage at the current job, $comm_i$ is the commuting time in minutes, and $wage_i(Q_k)$ are dummies for whether the worker's current wage is in the second, third, or fourth quartile of the industry-CZ wage distribution. Columns 3 and 4 show that conditional on commuting time and wage, workers at the bottom of the wage distribution spend more time searching, consistent with our model. Moreover, greater commuting time increases search.

In column 5 we run the regression with the total number of workers employed in the worker's industry and CZ instead of with the wage quartile dummies. As in the main appendix, workers' search effort conditional on current wage is higher when the local job market is denser. In column 6 we add commuting time as control. With that control the effect of local employment is still positive but is no longer significant at conventional levels.

Table S82: Effect of Local Labor Market on Search

	(1)	(2)	(3)	(4)	(5)	(6)
	$Apps_i$	$Search_i$	$Search_i$	$Search_i$	$Search_i$	$Search_i$
$\ln(wage_i)$	$-\mathbf{.0888}^{***}$	$-\mathbf{.0760}^{***}$		$-.0281$	$-\mathbf{.1078}^{***}$	$-\mathbf{.1111}^{*}$
	(.0157)	(.0159)		(.0266)	(.0204)	(.0207)
$\mathbb{I}(\text{Satisfaction}_i = 2)$	$-\mathbf{.4619}^{***}$	$-\mathbf{.7227}^{***}$				
	(.1166)	(.1114)				
$\mathbb{I}(\text{Satisfaction}_i = 3)$	$-\mathbf{.7153}^{***}$	$-\mathbf{1.082}^{***}$				
	(.1151)	(.1098)				
$\mathbb{I}(\text{Satisfaction}_i = 4)$	$-\mathbf{.8682}^{***}$	$-\mathbf{1.2285}^{***}$				
	(.1093)	(.1051)				
$\mathbb{I}(\text{Satisfaction}_i = 5)$	$-\mathbf{.9779}^{***}$	$-\mathbf{1.3820}^{***}$				
	(.1094)	(.1049)				
$\ln(comm_i)$			$\mathbf{.0315}^{**}$	$\mathbf{.0324}^{**}$		$\mathbf{.0283}^{*}$
			(.0144)	(.0144)		(.0146)
$wage_i(Q2)$			$-\mathbf{.1407}^{***}$	$-\mathbf{.1165}^{***}$		
			(.0419)	(.0465)		
$wage_i(Q3)$			$-\mathbf{.2235}^{***}$	$-\mathbf{.1884}^{***}$		
			(.0399)	(.0502)		
$wage_i(Q4)$			$-\mathbf{.3056}^{***}$	$-\mathbf{.2527}^{***}$		
			(.0401)	(.0617)		
$\ln(emp_i)$					$\mathbf{.0147}^{*}$	.0125
					(.0086)	(.0086)
Industry FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Age, Sex, Ed	Y	Y	Y	Y	Y	Y
Obs	4,619	4,619	4,152	4,152	4,153	4,153

Source: SCE and authors' calculations. Notes: Regressions are run on individual-level data for 2013-2020. $Apps_i$ is the IHS of the number of job applications sent by worker i in the last four weeks. $Search_i$ is the IHS of the number of hours spent searching for jobs in the last seven days. $\mathbb{I}(\text{Satisfaction}_i = k)$ is the level of total satisfaction with the current job, where $k = 2$ is "Somewhat dissatisfied" and satisfaction increases up to $k = 5$, which is "Very satisfied". $wage_i$ are the weekly earnings at the main job. $comm_i$ is the average time spent commuting to the main job each day. $wage_i(Qx)$ is a dummy for whether the worker's weekly earnings are in the x percentile of worker i's commuting zone by industry wage distribution from the ACS. emp_i is the total employment in worker i's industry in her commuting zone from the CBP. Industries are 2-digit NAICS industries. Age controls are dummies for < 25, $25 - 54$, and 55+ years. Sex is a dummy for males. Ed is a dummy for a bacherlor's degree.