Supplemental Material – Not for Publication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)
$\mathbb{I}_{j,East}$	$-$**.2609*****	$-$**.2695*****	$-$**.2467*****	$-$**.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

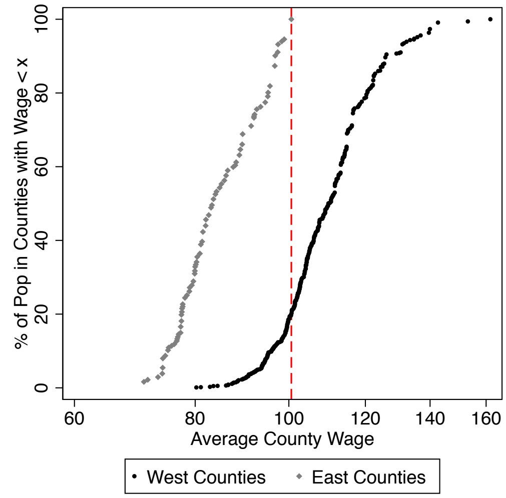
Source: BHP and authors' calculations. Notes: The table presents the estimates on the East Germany dummy from specification (1) for the period 2009-2014, where firms are weighted by size. $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors 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)
$\mathbb{I}_{j,East}$	$-$**.1600*****	$-$**.1876*****	$-$**.1942*****	$-$**.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.

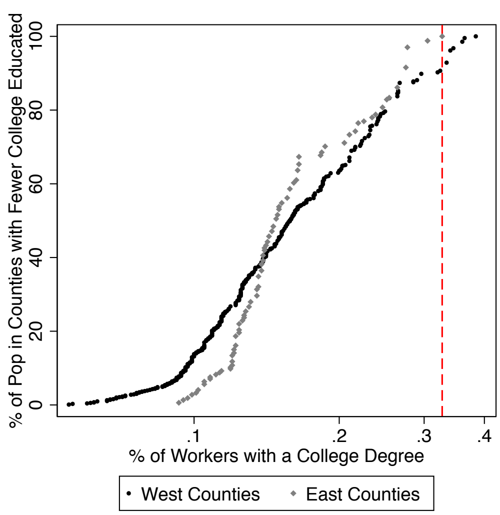
Figure S1: Cumulative Distribution Functions of Real Wages in East and West



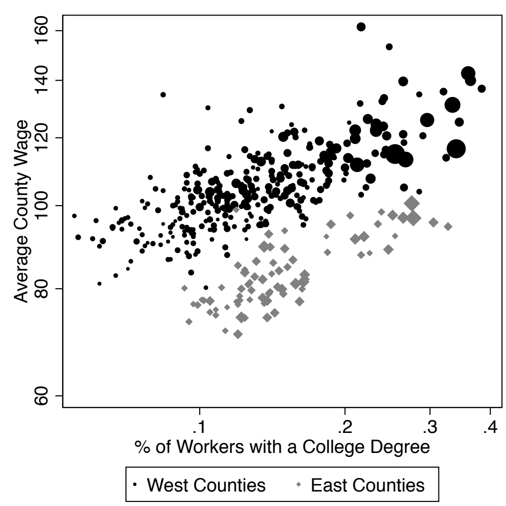
Source: BHP. Note: The figure shows the CDF of real wages across East and West German counties. Each dot is a county, where the steepness of the CDF is determined by the share of each region's full-time workers captured by the next county. Each county-level average wage is computed as a weighted average 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



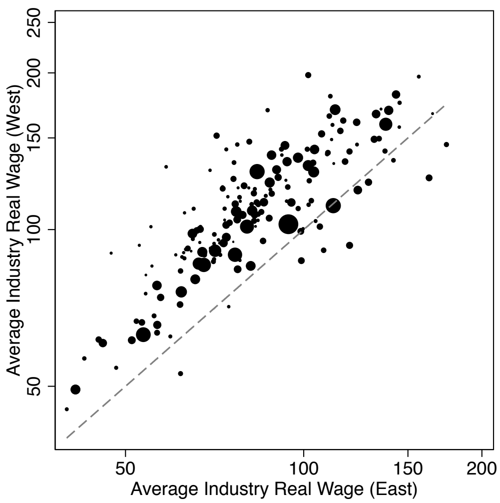
(b) Real Wage by Highly-Skilled Share Across Counties



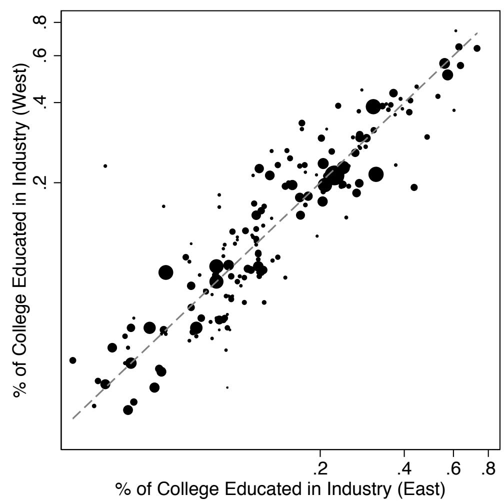
Source: BHP. Note: The left figure shows the CDF of the share of workers with a college degree in each county, where this share is calculated as the number of full-time workers with high qualification (az_hq_vz) divided by all full-time workers. Each dot is a county, where the steepness of the CDF is 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

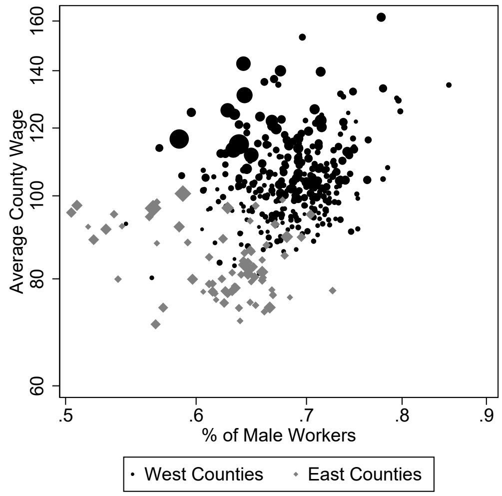


(b) Share of College-Educated by Industry in East vs. West



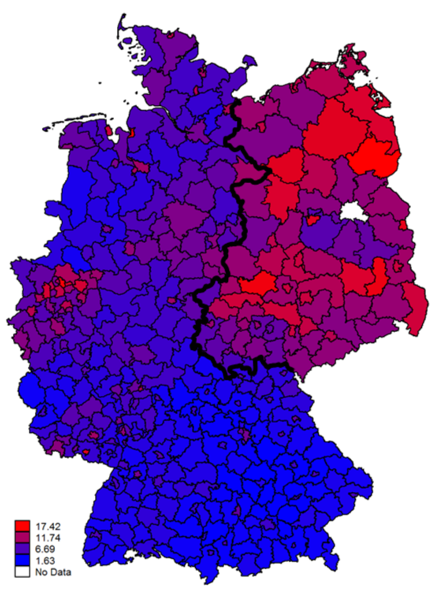
Source: BHP. Note: The left figure plots the average real wage in East Germany against the average real wage in West Germany at the industry-level. Each industry is a 3-digit WZ93 code, using the concordance by Eberle et al., 2011. Each industry-level average wage is computed as a weighted average real 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



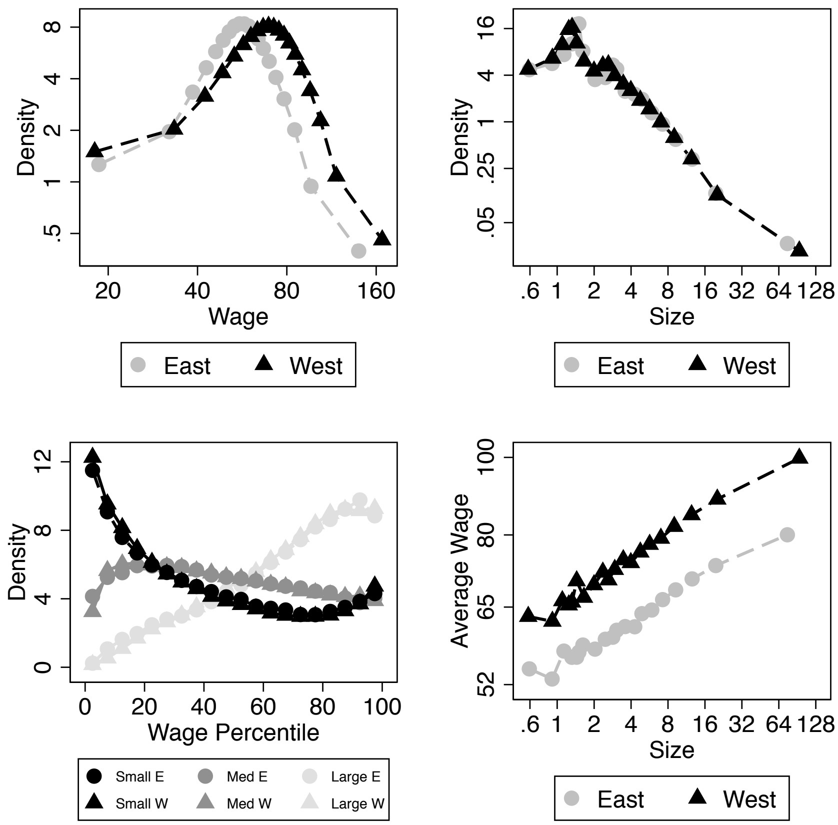
Source: BHP. Notes: The figure plots the share of full-time workers that are male in each county against the average real wage of the county. The average real wage in each county is computed as a weighted average over all firms in the county, using the number of full-time workers as weight. The size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

Figure S5: Unemployment



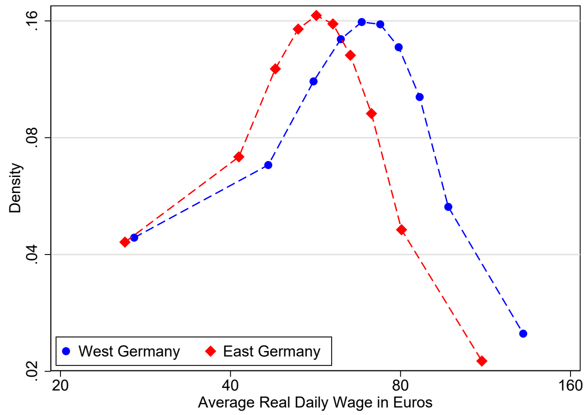
Source: Bundesagentur für Arbeit. Notes: The figure shows the average unemployment rate for each county in 2009-2014. Former East-West border is drawn in black for clarification. We exclude Berlin since we cannot assign it unambiguously to "East" or "West".

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.

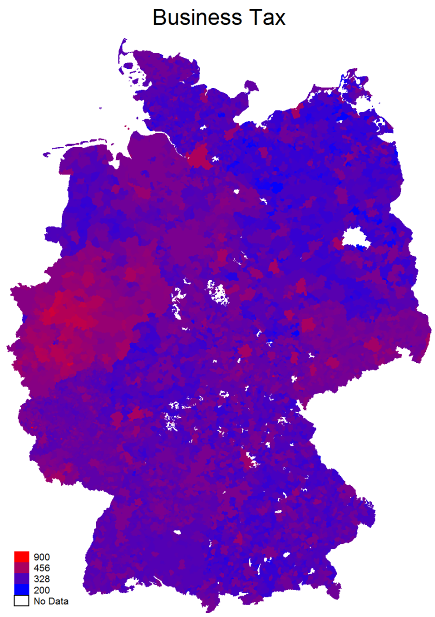
Figure S7: Firm Wage Distributions within County and Industry



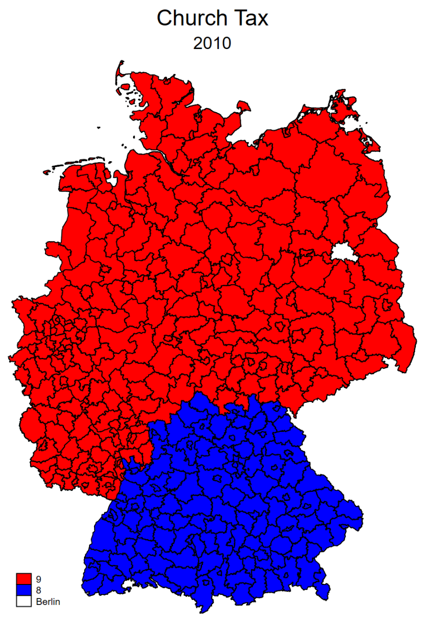
Source: BHP. Notes: The figure plots the densities of firm wages in East and in West Germany. The wage densities are residualized by regressing, for East and West Germany separately, the log real wage on 3-digit industry dummies, time dummies, county dummies, the share of male full-time workers, the 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

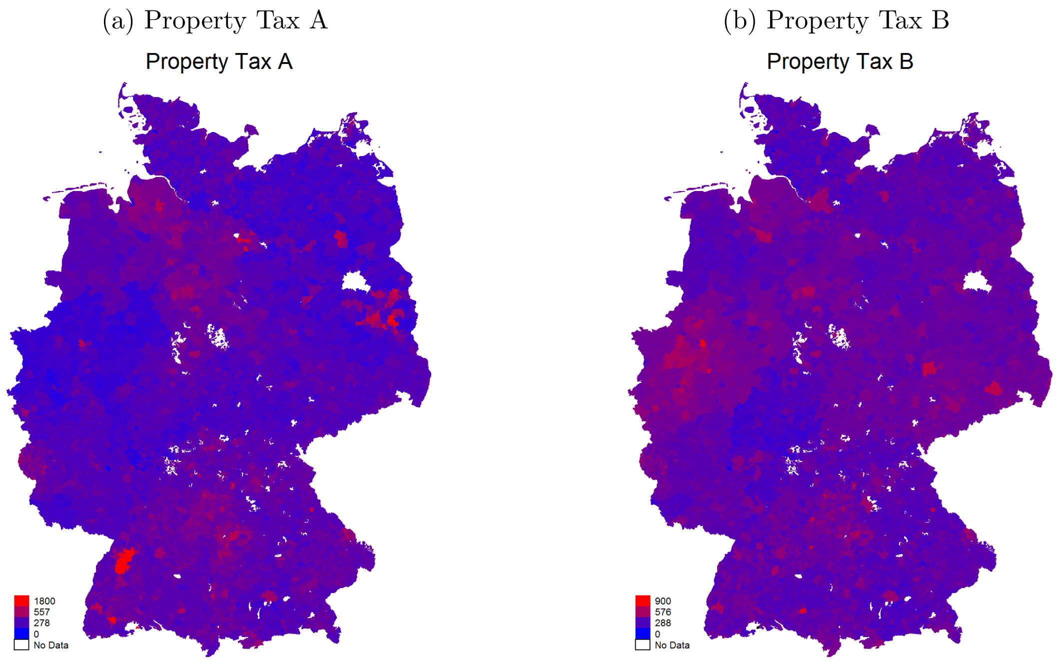


(b) Church Tax



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



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 $i \in \{\text{West, East}\}$, 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	$-.0040$	$\mathbf{-.0305}^{***}$	$\mathbf{.1698}^{***}$	$\mathbf{-.0160}^{**}$	.0066	$-.0036$
	(.0107)	(.0099)	(.0097)	(.0126)	(.0071)	(.0073)	(.0081)
$d_{it}^{WE,m}(\mathbb{I}_i^E = 0)$	.0023	$-.0072$	$\mathbf{-.0273}^{***}$	$\mathbf{.1734}^{***}$	.0051	$-.0015$	.0079
	(.0088)	(.0086)	(.0084)	(.0129)	(.0059)	(.0064)	(.0064)
$d_{it}^{EW,m}(\mathbb{I}_i^E = 1)$	$\mathbf{-.0163}^{***}$	$\mathbf{-.0335}^{***}$	$\mathbf{-.0468}^{***}$	$\mathbf{.3400}^{***}$	$\mathbf{.0096}^{***}$	$-.0008$	.0033
	(.0052)	(.0057)	(.0052)	(.0081)	(.0031)	(.0033)	(.0036)
$d_{it}^{WE,m}(\mathbb{I}_i^E = 1)$	.0038	$-.0039$	$-.0015$	.0125	$-.0057$	$\mathbf{-.0095}^{**}$	$-.0023$
	(.0066)	(.0072)	(.0067)	(.0085)	(.0042)	(.0045)	(.0050)
$d_{it}^{EW,c}(\mathbb{I}_i^E = 0)$	$\mathbf{-.0088}^{**}$	$\mathbf{-.0166}^{***}$	$\mathbf{-.0138}^{***}$	$\mathbf{.0721}^{***}$	$-.0044$	.0048	.0001
	(.0040)	(.0041)	(.0040)	(.0048)	(.0033)	(.0034)	(.0035)
$d_{it}^{WE,c}(\mathbb{I}_i^E = 0)$	$-.0017$	$-.0012$	$\mathbf{-.0231}^{***}$	$\mathbf{.0454}^{***}$	$\mathbf{-.0060}^{*}$	$-.0011$	$-.0004$
	(.0040)	(.0039)	(.0039)	(.0051)	(.0033)	(.0034)	(.0035)
$d_{it}^{EW,c}(\mathbb{I}_i^E = 1)$	$\mathbf{-.0104}^{***}$	$\mathbf{-.0240}^{***}$	$\mathbf{-.0323}^{***}$	$\mathbf{.1485}^{***}$	$\mathbf{-.0033}^{*}$	$\mathbf{-.0043}^{**}$	$\mathbf{-.0041}^{**}$
	(.0024)	(.0024)	(.0024)	(.0035)	(.0019)	(.0019)	(.0020)
$d_{it}^{WE,c}(\mathbb{I}_i^E = 1)$	$\mathbf{-.0128}^{***}$	$\mathbf{-.0133}^{***}$	$\mathbf{-.0190}^{***}$	$\mathbf{.0335}^{***}$	.0018	.0005	$\mathbf{-.0054}^{**}$
	(.0026)	(.0027)	(.0028)	(.0035)	(.0021)	(.0021)	(.0022)
$d_{it}^{EE}(\mathbb{I}_i^E = 0)$	$\mathbf{-.0188}^{***}$	$\mathbf{-.0200}^{***}$	$\mathbf{-.0389}^{***}$	$\mathbf{.0712}^{***}$	$\mathbf{.0056}^{***}$	$\mathbf{.0051}^{**}$	$\mathbf{.0049}^{**}$
	(.0025)	(.0026)	(.0025)	(.0031)	(.0021)	(.0021)	(.0023)
$d_{it}^{WW}(\mathbb{I}_i^E = 0)$	$\mathbf{-.0102}^{***}$	$\mathbf{-.0186}^{***}$	$\mathbf{-.0362}^{***}$	$\mathbf{.1247}^{***}$	$\mathbf{.0119}^{***}$	$\mathbf{.0082}^{***}$	$\mathbf{.0070}^{***}$
	(.0005)	(.0005)	(.0005)	(.0008)	(.0004)	(.0005)	(.0005)
$d_{it}^{EE}(\mathbb{I}_i^E = 1)$	$\mathbf{-.0134}^{***}$	$\mathbf{-.0199}^{***}$	$\mathbf{-.0319}^{***}$	$\mathbf{.0808}^{***}$	$\mathbf{.0034}^{***}$	$\mathbf{.0015}^{***}$	$\mathbf{.0031}^{***}$
	(.0006)	(.0007)	(.0007)	(.0010)	(.0005)	(.0006)	(.0006)
$d_{it}^{WW}(\mathbb{I}_i^E = 1)$	$\mathbf{-.0165}^{***}$	$\mathbf{-.0179}^{***}$	$\mathbf{-.0332}^{***}$	$\mathbf{.1222}^{***}$	$\mathbf{.0033}^{***}$	.0008	$-.0018$
	(.0017)	(.0017)	(.0016)	(.0021)	(.0012)	(.0013)	(.0014)
$\mathbb{I}_i^E$	$\mathbf{.0138}^{***}$	$\mathbf{.0130}^{***}$	$\mathbf{.0141}^{***}$	$\mathbf{.0015}^{***}$	$\mathbf{-.0015}^{***}$	$\mathbf{.0015}^{***}$	$\mathbf{.0027}^{***}$
	(.0005)	(.0005)	(.0005)	(.0005)	(.0004)	(.0004)	(.0005)
Work_{it}^E	$\mathbf{-.0049}^{***}$	$\mathbf{-.0056}^{***}$	$\mathbf{-.0028}^{***}$	$\mathbf{.0044}^{***}$	$\mathbf{.0027}^{***}$	$\mathbf{.0047}^{***}$	$\mathbf{.0043}^{***}$
	(.0006)	(.0006)	(.0006)	(.0007)	(.0006)	(.0006)	(.0006)
$\mathbb{I}_i^E \cdot \text{Work}_{it}^E$	$\mathbf{-.0133}^{***}$	$\mathbf{-.0122}^{***}$	$\mathbf{-.0166}^{***}$	$\mathbf{-.0052}^{***}$	.0010	$-.0008$	$\mathbf{-.0015}^{*}$
	(.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.

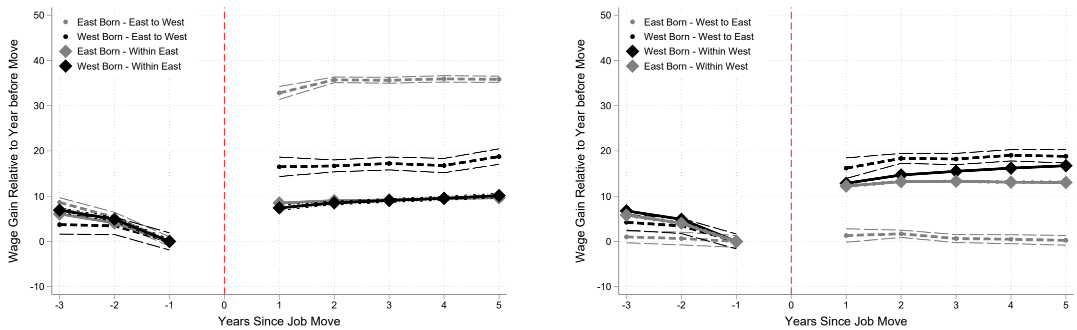
Table S8: Wage Gains of Job-to-Job Moves (With Individual FE)

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)			(2)	
			Home: West			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

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

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

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

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

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

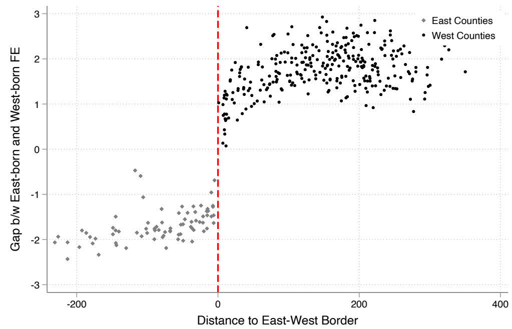
where $\mathbb{I}^h$ is a set of dummies for the worker's home location, $\mathbb{H} = \{SW, NE, SE\}$, and the dummies $\mathbb{I}_k$ capture moves between East and West Germany in the same way as before, with $\mathbb{K} = \{R(o) \neq R(d), R(o) = h, R(d) = h\}$. We also define $\mathbb{M} = \{L(o) \neq L(d), L(o) = h, L(d) = h\}$, 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, $\theta^i_j = 1$, $\tau^i_j = \tau_j$, $\delta^i_j = \delta$, $b^i_j \tau^i_j P_j^{-1} = \hat{b}$, and $R^i_j \tau^i_j P_j^{-1} = \hat{R}$ for all i and j, $\nu = 1$, $\chi = 0$, and $\sigma \to 0$, then the ODEs for the wage functions simplify to*

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

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

Proof. Define the real wage, adjusted for amenities, as $\hat{w} \equiv w \tau_j P_j^{-1}$, where we have used that $\tau^i_j = \tau_j$. By assumption, $\hat{b} \equiv b^i_j \tau_j P_j^{-1}$ is constant across regions. Define $\hat{F}_j(\hat{w}) \equiv F_j(w \tau_j P_j^{-1})$. 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 $\hat{p} \equiv p \tau_j P_j^{-1}$. The firm's maximization problem (9) becomes

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

for all j, where $\hat{l}\left(\hat{w}\right) \equiv l_j(w\tau_j P_j^{-1})$. From $a_{jx}^i(s_x) = 1$ 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 $\hat{R} \equiv R_j^i \tau_j P_j^{-1}$ is constant across regions by assumption. Since $\delta_j^i = \delta$, 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

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

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

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

and

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

where $\tilde{E}(\hat{p}) \equiv \sum_{x\in\mathbb{J}} \tilde{E}_x\left(\hat{p}\right)$ 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

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

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

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

and hence

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

The mass of unemployed is given from (19) by

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

Substituting these expressions into (50) gives

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

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

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

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^s_{it}	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

	Move to Location:	NW	SW	NE	SE
Birth Location	Current Work Location				
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

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

where y^{size}_{jlt} 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, $\hat{\epsilon}^{size}_{jlt}$. We add back the mean log number of workers in each location, $\overline{\ln(y^{size}_{jlt})}$, to obtain a cleaned number of workers, $\hat{y}^{size}_{jlt} = \exp[\overline{\ln(y^{size}_{jlt})} + \hat{\epsilon}^{size}_{jlt}]$. 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, $\hat{\epsilon}_{ilt}^{wage}$, and for the separation dummy, $\hat{\epsilon}_{ilt}^{sep}$, and add back the mean of each variable in each location, $\overline{\ln(w_{ilt})}$ and $\overline{d_{ilt}^{sep}}$, to obtain a cleaned log wage, $\ln(\hat{w}_{ilt}) = \overline{\ln(w_{ilt})} + \hat{\epsilon}_{ilt}^{wage}$ and a cleaned separation dummy $\hat{d}_{ilt}^{sep} = \overline{\ln(d_{ilt}^{sep})} + \hat{\epsilon}_{ilt}^{sep}$. We then regress the residualized separation dummy on the residualized log wages for each location

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

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 $\hat{d}_{ilt}^{sep}$ and $\ln(\hat{w}_{ilt})$ in Figure A11, panel (c).

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

Dep. var.: $\hat{d}_{irt}^{sep}$	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

	New Job Location:	NW	SW	NE	SE
Home Location	Current Job Location				
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 $\left(p,p'\right)$ and worker type i,

and the job applications:

$$\left\{\tilde{\mu}^{E,i}_{jx}\left(p,p';k\right),\tilde{\mu}^{U,i}_{jx}\left(b,p';k\right)\right\}$$
$$\left\{\tilde{a}^{E,i}_{jx}\left(p;k\right),\tilde{a}^{U,i}_{jx}\left(b;k\right)\right\}_{j\in\mathbb{J},x\in\mathbb{J},i\in\mathbb{I}}.$$

3. Given $\left\{\tilde{\mu}^{E,i}_{jx}\left(p,p';k\right),\tilde{\mu}^{U,i}_{jx}\left(b,p';k\right),\tilde{a}^{E,i}_{jx}\left(p;k\right),\tilde{a}^{U,i}_{jx}\left(b;k\right)\right\}_{j\in\mathbb{J},x\in\mathbb{J},i\in\mathbb{I}}$, we use equation (16) to solve for $\left\{\tilde{q}^{i}_{j}\left(p;k\right)\right\}_{j\in\mathbb{J},i\in\mathbb{I}}$ and then iterate through equations (15), (17), and (18) until convergence to get a new guess for the firm size per vacancy $\left\{\tilde{l}^{i}_{j}\left(p;k+1\right)\right\}_{j\in\mathbb{J},i\in\mathbb{I}}$ that is consistent with the steady state employment distributions $\tilde{E}^{i}_{j}\left(p;k\right)$ and the probability of accepting offers $\tilde{\mathcal{P}}^{i}_{j}(p;k)$.

4. Finally, using $\left\{\tilde{l}^{i}_{j}\left(p;k\right),\tilde{q}^{i}_{j}\left(p;k\right)\right\}_{j\in\mathbb{J},x\in\mathbb{J},i\in\mathbb{I}}$, 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

$$\left\{w_j\left(p;k+1\right),v_j\left(p;k+1\right),\vartheta_j\left(k+1\right),\tilde{l}^{i}_{j}\left(p;k+1\right)\right\}_{j\in\mathbb{J},i\in\mathbb{I}}$$

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

$$\phi^* \quad = \quad \arg\min_{\phi \in \mathbb{F}} \mathcal{L}(\phi) \tag{68}$$

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.

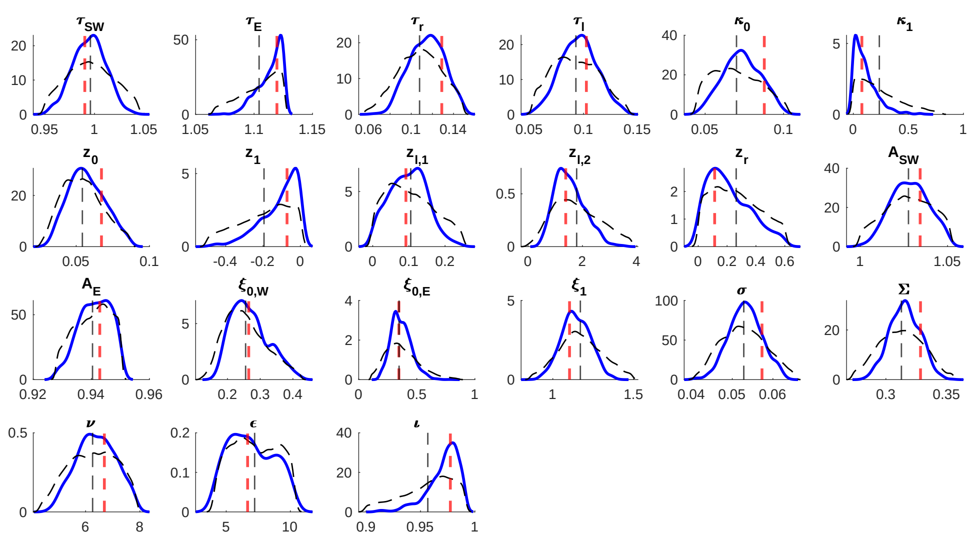
Finally, Tables S37 and S38 include all the primitive parameters and Figure S20 compares the outcomes of the three estimations and confirms that the biggest difference is for the moving costs.

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	/	/	/

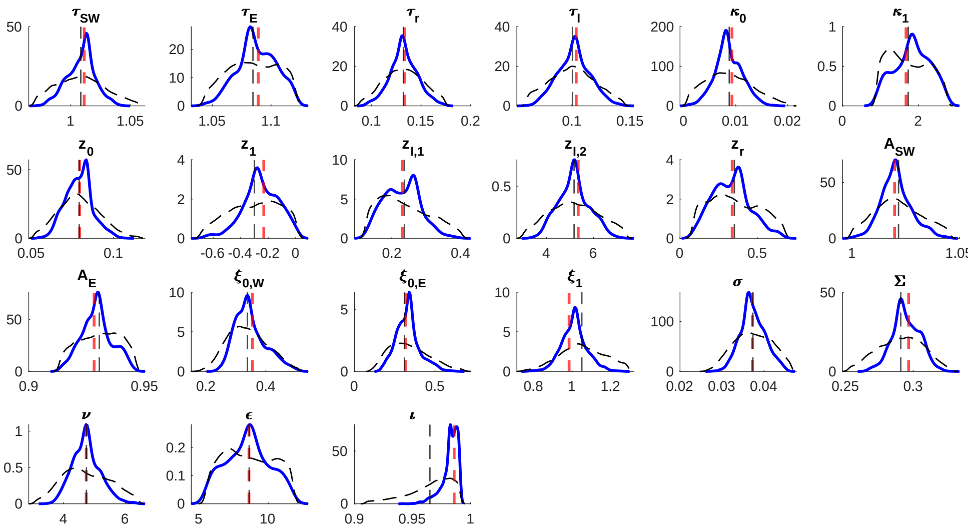
Notes: the table reports the moments used in the estimation and highlights whether they differ across the three estimations. If the moments used is identical across the three estimation, we include a slash symbol. Otherwise, we specify how the moments differ. Specifically, "Benchmark", "Migration", and "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



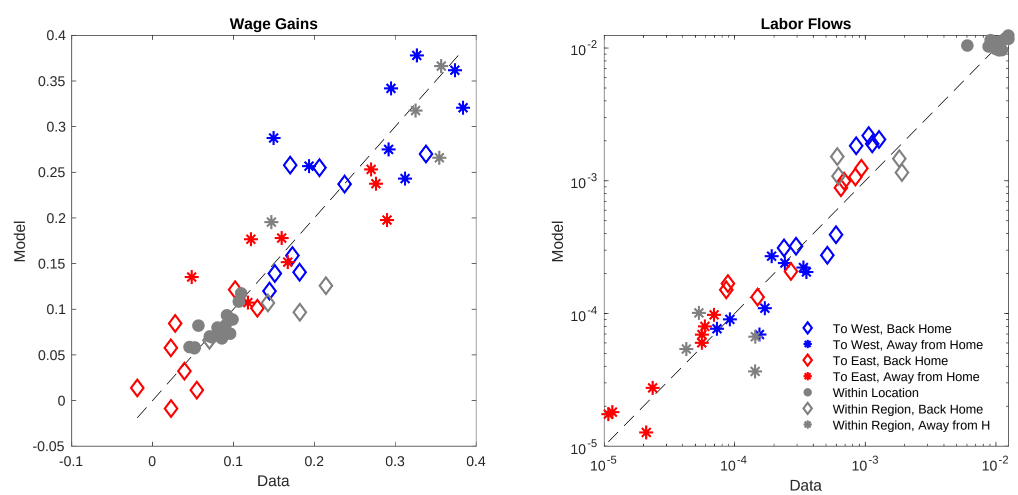
Notes: The figure shows the outcomes of the estimation for the "Only Migration Moves" estimation. Each panel shows a different one of the 21 estimated parameters. As described in the text, the black dashed and blue lines show the densities for different sub-sets of parameter draws. The red vertical lines 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



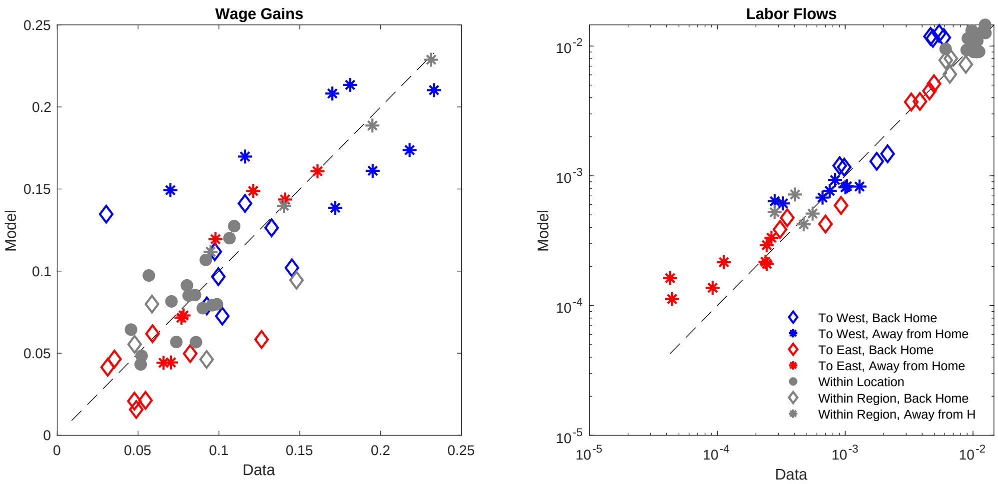
Notes: The figure shows the outcomes of the estimation for the "All Moves" estimation. Each panel shows a different one of the 21 estimated parameters. As described in the text, the black dashed and blue lines show the densities for different sub-sets of parameter draws. The red vertical lines are our 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



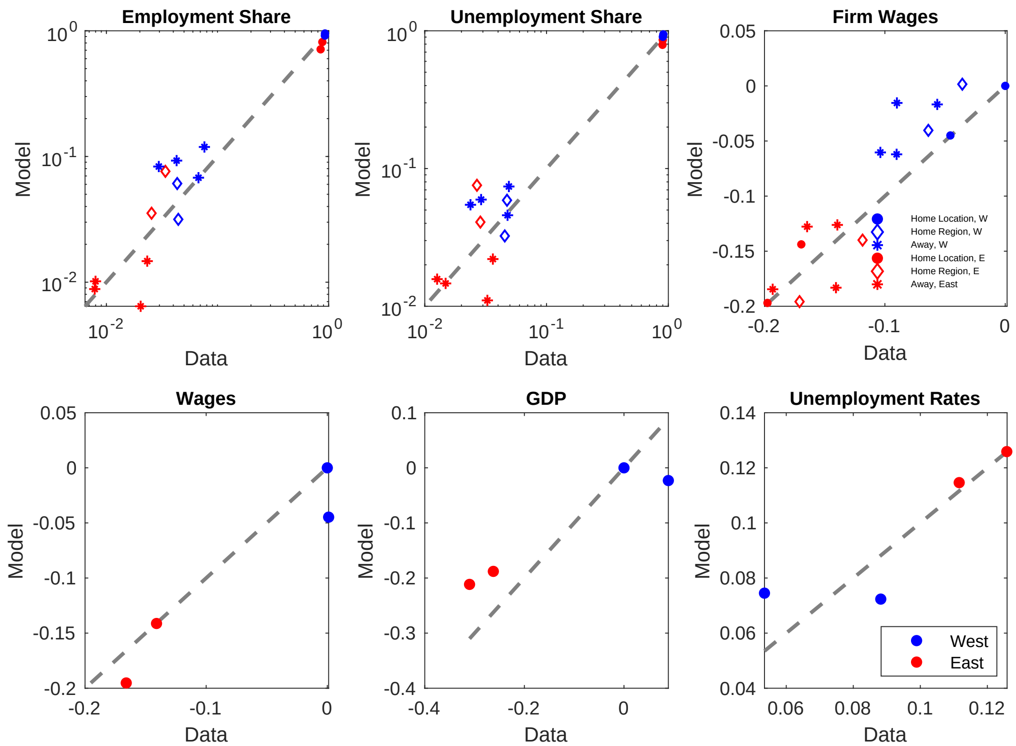
Notes: The left panel shows the average wage gains of different types of job-to-job moves in the data (x-axis) against the average wage gains in the model (y-axis) for the "Only Migration Moves" alternative. The right panel shows the frequency of each direction of the job-to-job move in the data (x-axis) 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



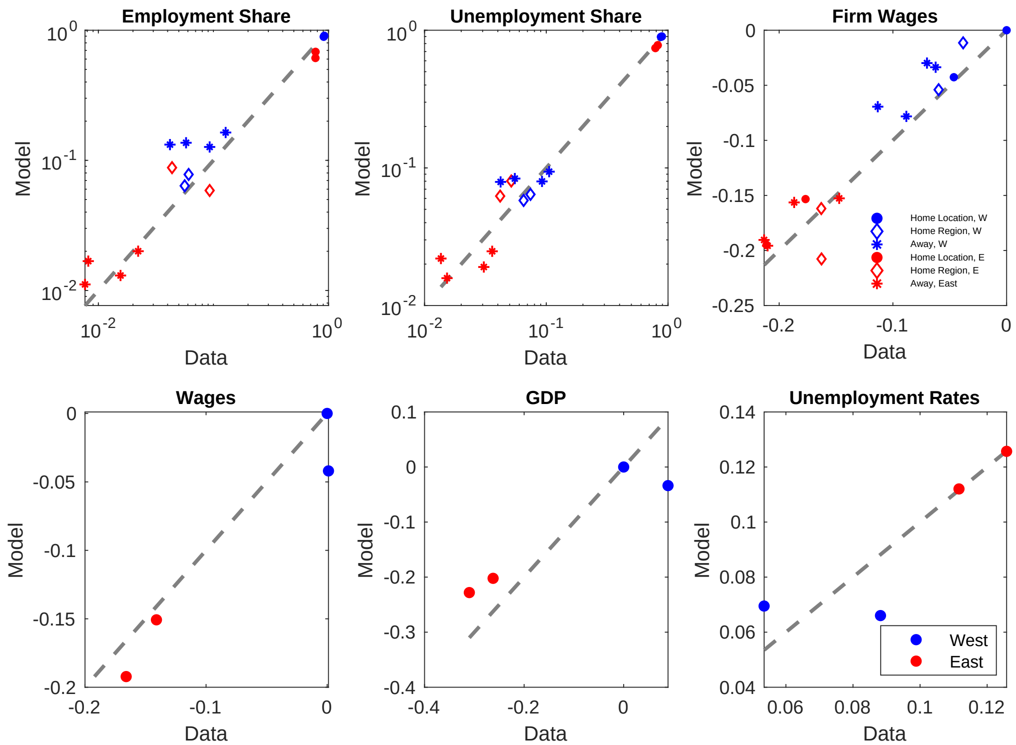
Notes: The left panel shows the average wage gains of different types of job-to-job moves in the data (x-axis) against the average wage gains in the model (y-axis) for the "All Moves" alternative. The right panel shows the frequency of each direction of the job-to-job move in the data (x-axis) against 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



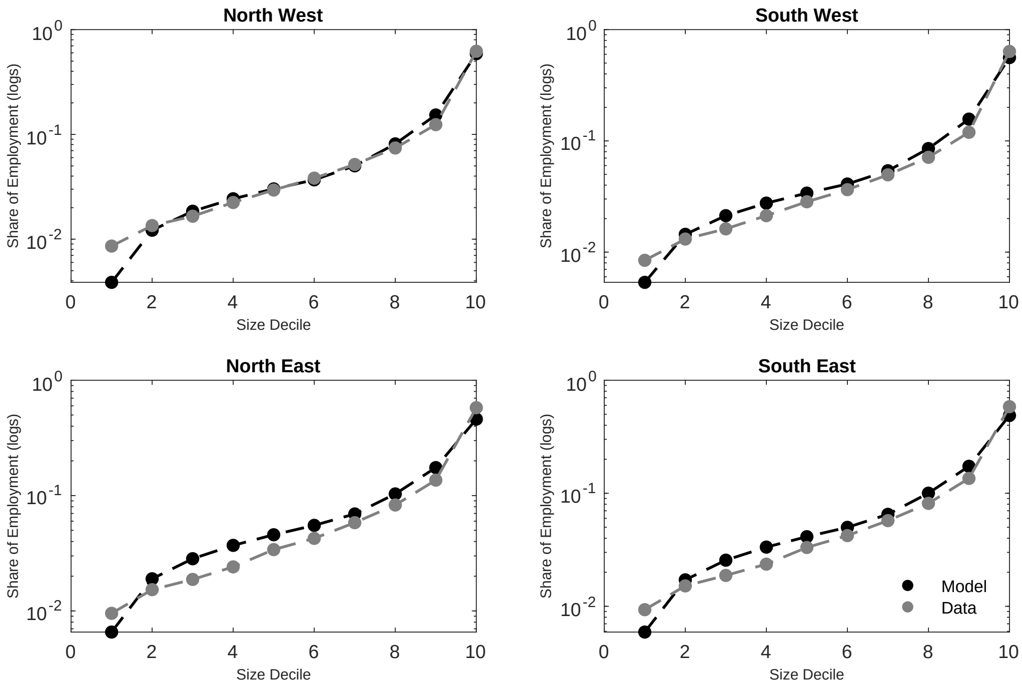
Notes: The figure graphs the value of various moments in the model against the same moments in the data for the "Only Migration Moves" estimation. The construction of these moments is described in Supplemental Appendices Q.2.3 to Q.2.8. Each dot corresponds to one moment. The top left panel shows the 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



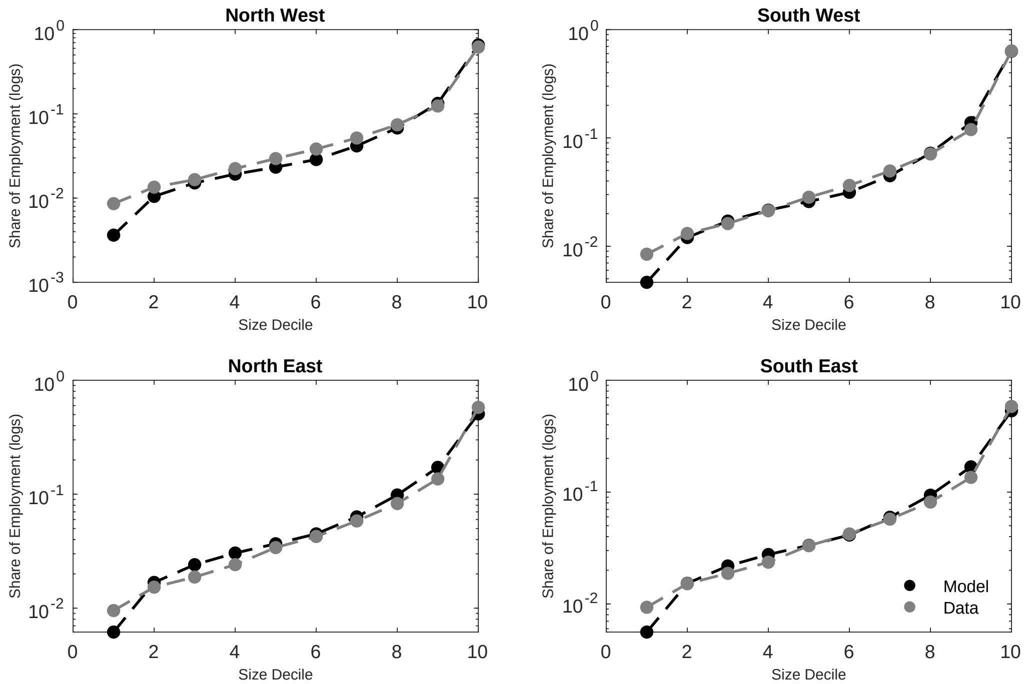
Notes: The figure graphs the value of various moments in the model against the same moments in the data for the "All Moves" estimation. The construction of these moments is described in Supplemental Appendices Q.2.3 to Q.2.8. Each dot corresponds to one moment. The top left panel shows the share of employed 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)	b/w locations (closest to furthest locations)	5.i) not to home region: $z_0 e^{-z_1 dist_{jx}}$	6.68% to 6.03%
		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%

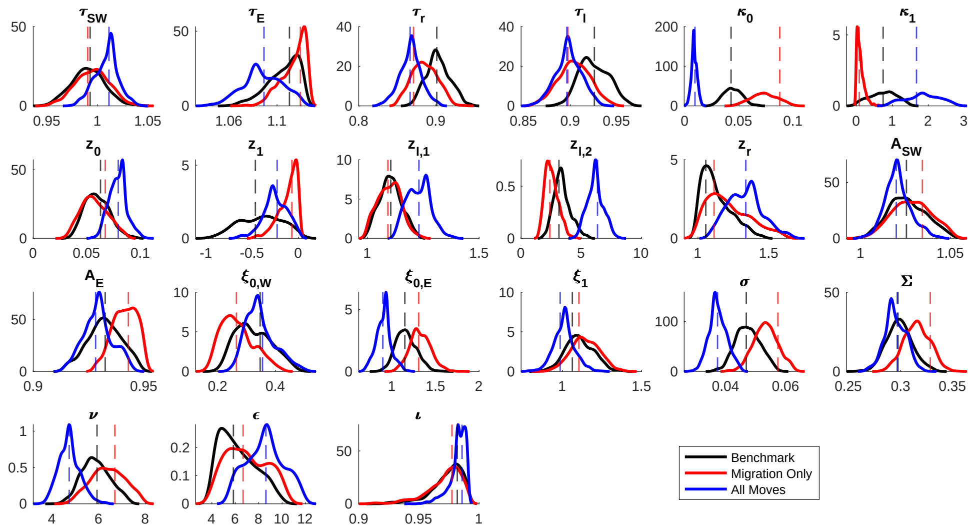
Notes: The table shows the estimated values of the spatial frictions in the "All Moves" estimation. All parameters used to compute them, according to the formula included in each row, are in Table S38. Row 1 provides a range of the estimated moving costs, ranging from costs for moves between the closest 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

		Share Residing in Current Location	
Birth Location	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.

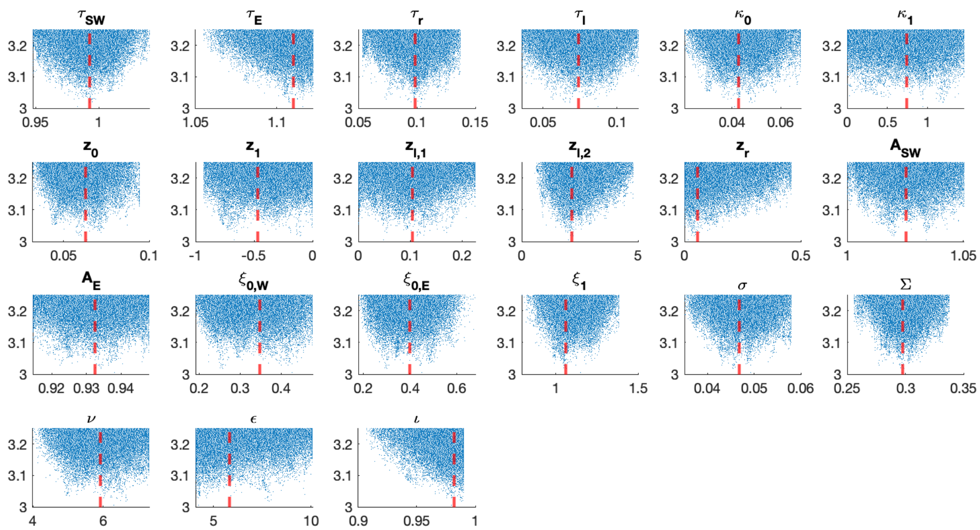
Table S80: Average Ratio of Firm Profits to Labor Costs by Location – All Moves

	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.

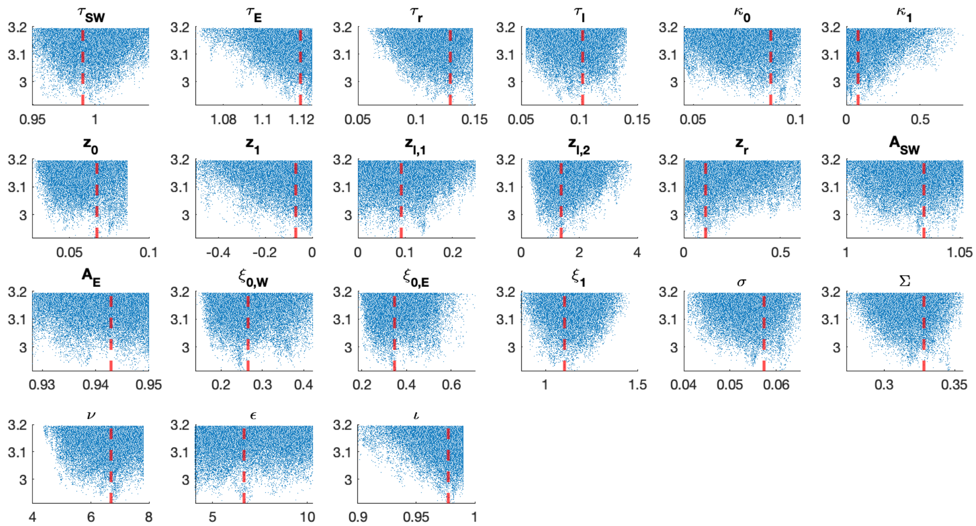
U.15 Likelihood Functions around Estimated Parameters

Figure S21: Likelihood Plots; Benchmark



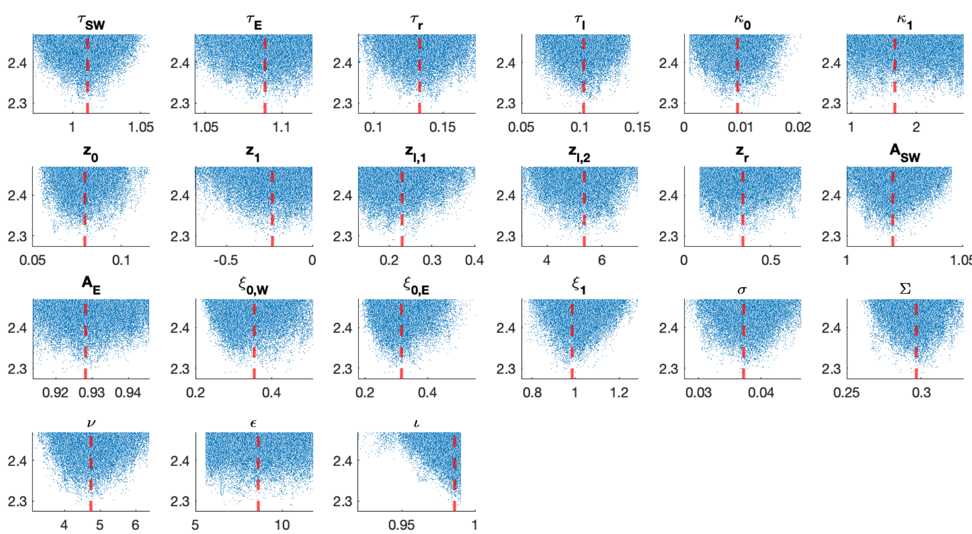
Notes: The table presents on the y-axis the draws of the best 10,000 values of the likelihood functions along the final estimation chain. On the x-axis, values of each one of the 21 primitive parameters are reported. We highlight with a red dotted line the estimated values for each parameter. If the 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.

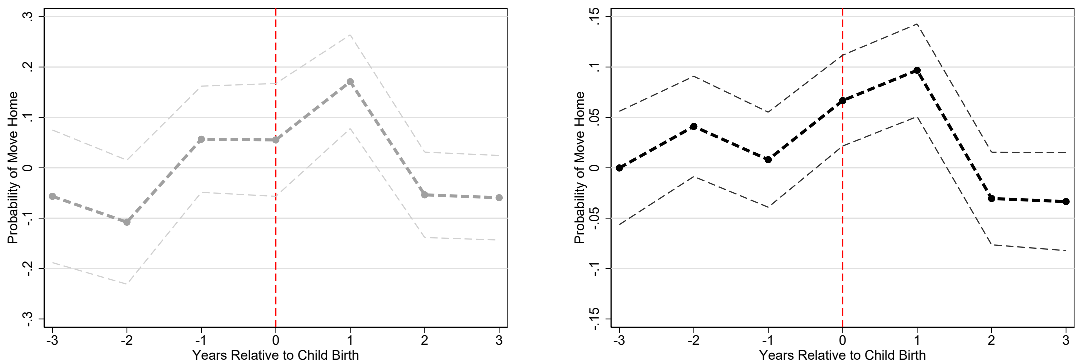
We find a significant spike of return moves one year after the birth of a child, thus suggesting that young parents might be more willing to move back home, possibly to benefit from childcare support from their own parents. The finding suggests that familial ties may be important in explaining workers' 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).

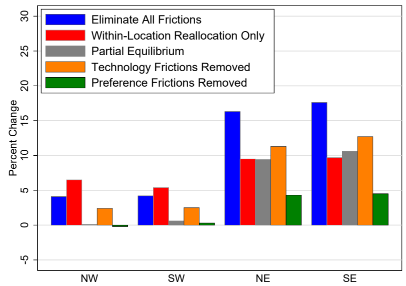
parameters (Panels (b) and (c)). For these two statistics, the allocation of labor within location is less relevant: removing spatial frictions mostly changes the value functions because workers receive more job opportunities and no longer pay the moving or utility cost, rather than because of within-location 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

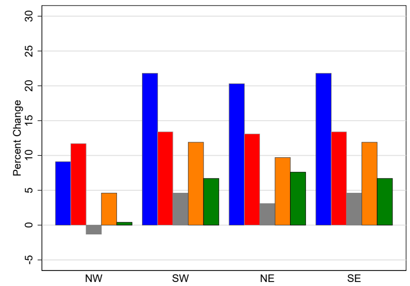
			All Frictions	w/i Locations	Partial Eq.	Technology	Preferences
			(1)	(2)	(3)	(4)	(5)
			Panel (a): Aggregate				
Overall	(1)	Output pc	+ 4.7 %	+ 6.6 %	+ 0.5 %	+ 2.7 %	+ 0.7 %
	(2)	Value Function	+ 37.0 %	+ 37.1 %	+ 22.0 %	+ 25.1 %	+ 2.9 %
	(3)	Wage	+ 9.1 %	+ 11.3 %	- 2.1 %	+ 3.8 %	+ 1.7 %
	(4)	Real 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

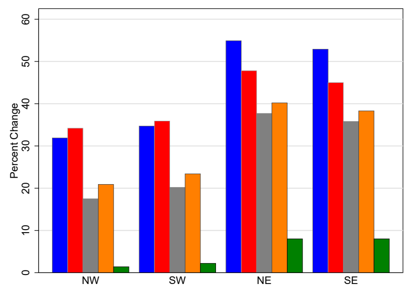
(a) Change in Output per Capita



(b) Change in Real Wage



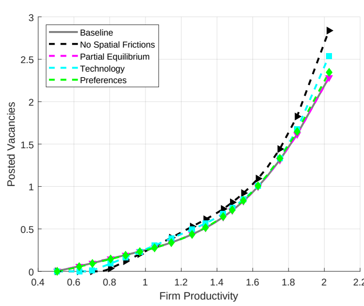
(c) Change in Value Function



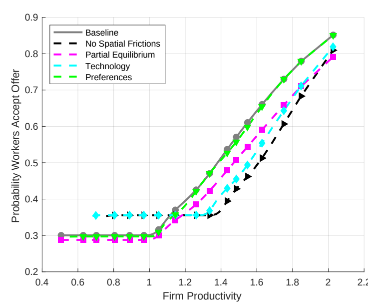
Notes: Figure shows the effects of various exercises, shown with the different-colored bars, on three outcomes: output per worker (top-left), real wage (top-right), and average value (bottom). Bars show percentage change relative to the baseline economy.

Figure S26: Margins of Employment, West Germany

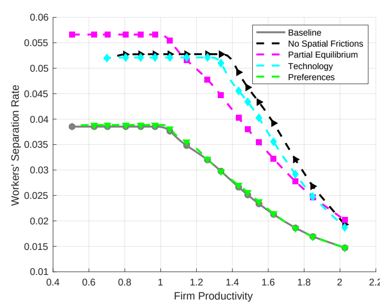
(a) Posted Vacancies



(b) Acceptance Probability



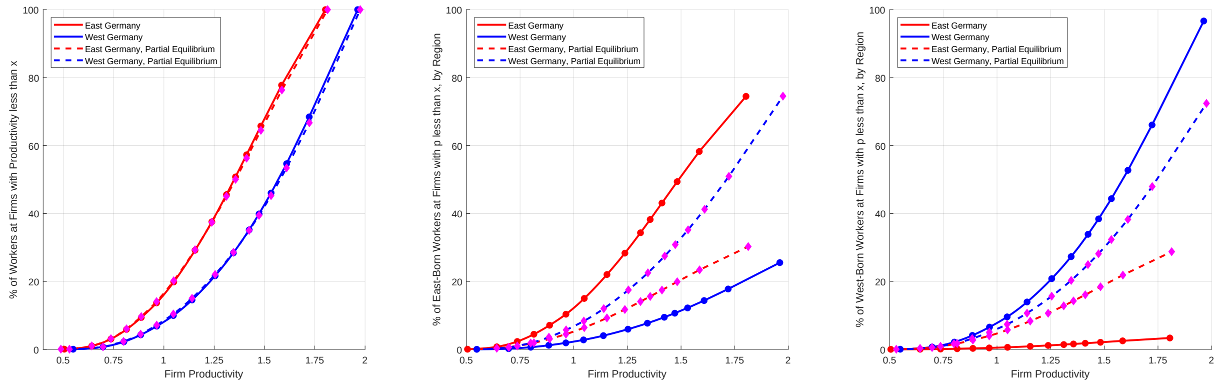
(c) Separation Rate



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

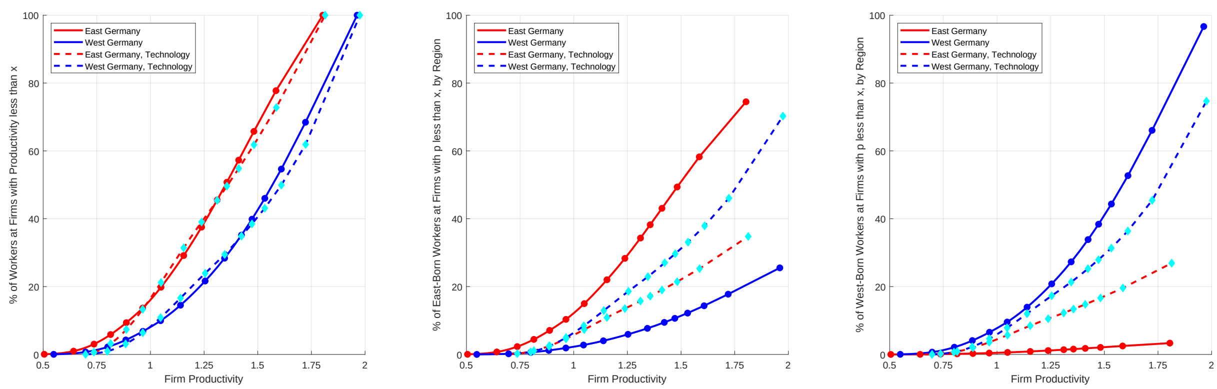
(a) All Workers (b) East Germans (c) West Germans



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

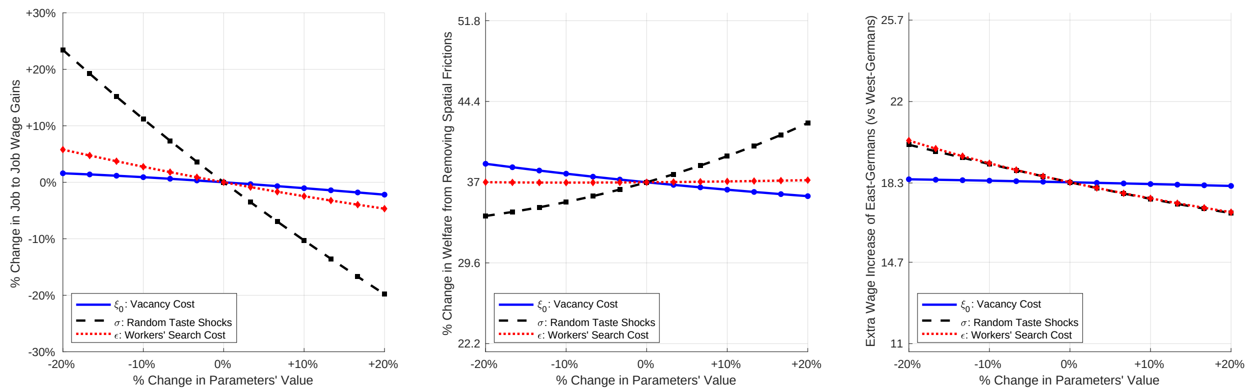
(a) All Workers (b) East Germans (c) West Germans



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

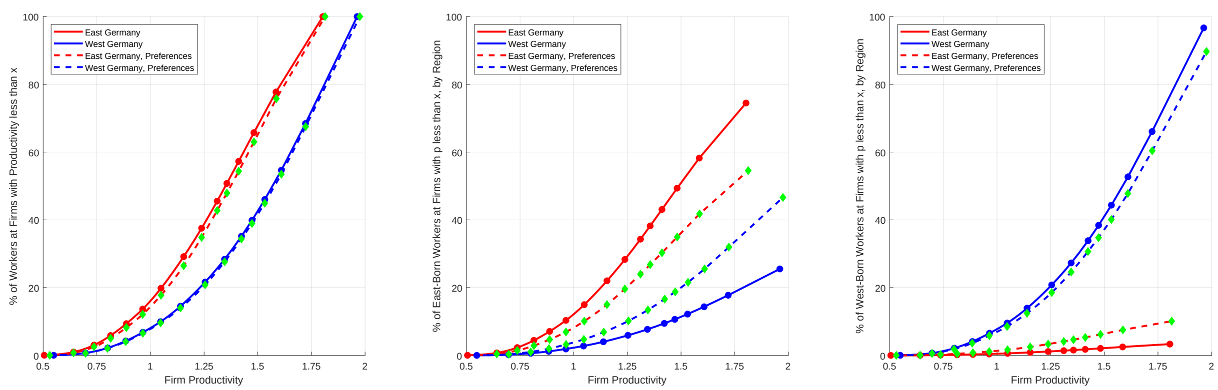
(a) Within-Location Wage Gains (b) Welfare Gains (c) Wage Gains of East Germans



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.