NBER WORKING PAPER SERIES

LABOR MISALLOCATION ACROSS FIRMS AND REGIONS

Sebastian Heise
Tommaso Porzio

Working Paper 30298
http://www.nber.org/papers/w30298

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2022

The views and opinions expressed in this work do not necessarily represent the views of the Federal Reserve Bank of New York. This study uses the weakly anonymous Establishment History Panel (Years 1975 - 2014) and the Linked-Employer-Employee Data (LIAB) Longitudinal Model 1993-2014 (LIAB LM 9314). Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and remote data access. The study also uses data made available by the German Socio-Economic Panel Study at the German Institute for Economic Research (DIW), Berlin. Neither the original collectors of the data nor the archive bear any responsibility for the analyses or interpretations presented here. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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July 2022
JEL No. J6,O1,R1

ABSTRACT

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

Sebastian Heise
Federal Reserve Bank of New York
Research and Statistics Group
33 Liberty Street
New York, NY 10045
sebastian.heise@ny.frb.org

Tommaso Porzio
Columbia Business School
3022 Broadway
Uris Hall 824
New York, NY 10027
and NBER
tommaso.porzio@columbia.edu

A data appendix is available at http://www.nber.org/data-appendix/w30298

1 Introduction

In many countries, large differences in real wages and labor productivity across regions have persisted for long periods of time.[1] These persistent differences suggest the presence of spatial frictions, such as moving costs, that limit the ability of workers to arbitrage the gaps away by migrating towards more productive regions. A large literature has shown that such frictions to labor mobility could entail large aggregate losses by misallocating labor across space.[2]

In this paper, we study and quantify a new margin through which spatial frictions misallocate labor and reduce aggregate productivity. We develop a general equilibrium framework that embeds frictional labor markets as in Burdett and Mortensen (1998) within a multi-region economy subject to a variety of spatial barriers. Estimating the model with matched employer-employee data from Germany, we find that, beyond misallocating labor across space, spatial frictions have an additional impact on the worker allocation: they misallocate labor across firms *within* regions.

In a frictional labor market, spatial barriers deprive workers of job opportunities in other regions, which they could use to move up the job ladder, thus slowing the reallocation of labor towards more productive firms. Additionally, spatial barriers increase firms' local monopsony power, which allows in particular low productivity firms to stay in business and to attract workers. We estimate that the aggregate losses due to these mechanisms in Germany amount to about 5% of GDP. These losses depend crucially on the details of the local labor market: as we show, two economies could exhibit the same wage or productivity gap between regions, yet the aggregate gains from removing spatial frictions could vary dramatically between the two economies dependent on their local labor market frictions.

In the first part of the paper, we use micro data from the German Federal Employment Agency to document three sets of facts, which motivate our focus on the joint allocation of labor across firms and regions and justify the ingredients of our model.

First, we use the Establishment History Panel (BHP), a 50% sample of all establishments in Germany, to study the distribution of wages and employment within and between regions. We document a large real wage gap between East and West Germany, but also significant heterogeneity in wages across firms *within* the two regions. Overall, it would be possible to completely close the regional wage gap by just reallocating labor within East Germany towards high-wage firms.

Second, we use the Linked Employer-Employee Data (LIAB) to study workers' wage gains as they climb the job ladder. We show that East Germans get very large wage increases when moving West, suggesting substantial gains from regional integration. At the same time, workers experience sizable wage gains for any job-to-job move, even within region, thus implying that

[1] Examples are the Italian Mezzogiorno, Andalusia in Spain, and the East of Germany.

[2] We discuss the relevant literature in detail in a section below.

frictions hindering within-region mobility could be as costly as those limiting migration towards high productivity regions.

Third, we use again the LIAB data to study workers' flows. We show that the job ladder is distorted. Workers switch jobs mostly locally and exhibit home bias (i.e., workers have a preference for their home region), leading to a job ladder that is characterized by frequent return migration of workers that have left their home region.

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

Our model allows us to structurally identify the different spatial frictions and to isolate them from general labor market frictions. Separating the different types of spatial frictions is important as they have distinct aggregate effects on the economy and are amenable to different policy interventions.[3] While all model parameters and frictions are jointly identified, we provide a heuristic identification argument. First, the unobservable distribution of job offers in each region is disciplined by within-region data on the joint distribution of wages and firm size, the average wage gains of job movers, and the frequency of job changes. Given a set of within-region offer distributions, the spatial frictions are identified by comparing the wage gains and job flows across regions to their within-region analogues. Higher observed wage gains for movers into a region compared to movers within that region reflect the presence of moving costs, as cross-region job switchers need to be compensated to move. Similarly, higher observed wage gains for workers moving out of their home region relative to other worker types making the same move identify home preferences. The relative frequency of job switches, instead, disciplines the spatial search costs. Relatively lower worker flows across regions, compared to between firms within region, indicate in our model that workers are less able to apply for jobs in other regions.

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

[3]For example, tax vouchers to limit moving expenses may increase mobility if spatial frictions represent moving costs, but may be less effective if spatial frictions are due to worker preferences for their home region, which are difficult to affect with policy.

with 21 parameters being used to match 305 micro and aggregate moments.

Our model estimates imply non-negligible spatial barriers, especially due to the limited ability of workers to access job opportunities that are further away, consistent with evidence that labor markets are primarily local (e.g., Manning and Petrongolo (2017)). For a given search effort, workers generate only 1/20th as many job applications when searching for jobs across locations as within. We estimate a direct cost of moving between any two locations of 3.1%-5.3% of life-time income (dependent on the distance of the move), and find that workers need to be paid, everything else equal, 7.4% of their yearly income to work away from their home location and maintain the same utility. These relatively small moving costs and home biases reflect our model's ability to separate their impact from spatial search frictions and from general labor market frictions.

In the third part of the paper, we compute a series of counterfactual equilibria to quantify the aggregate and distributional costs of spatial frictions. Removing all spatial frictions, including workers' home bias, would raise GDP per capita in Germany by almost 5%, and average real wages by 9%. These sizable gains are due to improvements in the allocation of labor *within* each location, rather than due to net migration from low to high productivity areas. Removing spatial frictions reduces firms' local monopsony power by exposing them to more competition from other locations, which forces unproductive firms to shrink or to exit the market and reallocates labor towards high productivity firms. Moreover, workers now have more job opportunities as they climb an integrated Germany-wide job ladder. Our empirical estimates indicate that the aggregate gains are mainly due to the former channel, i.e., the endogenous response of firms to the changes in the competitive environment. If we hold fixed firms' wage posting and vacancies, removing spatial frictions generates only a modest increase of 0.5% in output per capita, significantly smaller than the 5% gain including firms' equilibrium response.

The gains are not equally distributed across locations and workers' types. When spatial frictions are removed, East Germany sees an increase in output per capita of 17%, while aggregate gains in the West are only 4%. Similarly, East Germans see their wage rise by almost 25%, while West Germans gain less than 9%. Both the reallocation of labor within locations and across locations are important for these distributional effects. Labor reallocation within East Germany is larger than in the West since there are more unproductive firms there, which are more affected by spatial frictions. Reallocation of workers across locations is important because eliminating spatial frictions reduces dramatically the sorting of East and West Germans towards their home region, allowing more East Germans to benefit from the higher wages paid in the West. Moreover, since we estimate that West Germans have higher unobserved skills, migration of some West Germans to the East raises East German output and wages by increasing the average skill-level of the East German labor force.

Our results remain qualitatively unchanged when we eliminate only the spatial frictions generated by technological parameters (the moving cost and the spatial search frictions), while keeping in place workers' preference for their home region. However, we find strong complementarities between technological spatial frictions and workers' home bias. Summing over the gains from removing the two types of spatial frictions separately, we obtain only about half of the gains from removing both sources of frictions at the same time. Thus, the gains from an integrated labor market are largest when workers have access to opportunities to move to more productive locations (technology), but are also willing to accept these opportunities (preferences).

Our main conclusions are robust to allowing for more than four locations. As we increase the number of geographic units, we continue to find large aggregate gains due to the within-location reallocation of workers, although the estimated gains from reallocation of workers across locations also rise. Additionally, increasing the number of firms and workers in a location has virtually no effect on the location's aggregate gains from removing spatial frictions.

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

Literature. We build on a large body of work that has studied the impact of factor misallocation on aggregate productivity (e.g., Hsieh and Klenow (2009); Restuccia and Rogerson (2013)). In particular, we fit within a growing quantitative macro literature studying the role of labor market frictions in misallocating labor (Bilal, Engbom, Mongey, and Violante (2019, 2021); Engbom (2020); Elsby and Gottfries (2022); Martellini (2022)). Our contribution is to study jointly the allocation of labor across firms and space, and to quantify the role of spatial frictions in shaping the competitive environment in the local labor market, leading to misallocation of labor across firms and within regions. Our focus on spatial frictions in the labor market is motivated by recent work showing that workers direct most of their search effort locally (e.g., Manning and Petrongolo (2017)).[4]

Our paper also builds on the quantitative spatial literature that has developed general equilibrium frameworks to study the aggregate and distributional impacts of barriers to the mobility of labor across space, industries, and occupations (e.g., Caliendo, Dvorkin, and Parro (2019); Bryan and Morten (2019); Hsieh, Hurst, Jones, and Klenow (2019)).[5] Our contribution to this

[4]See also Schmutz and Sidibé (2018) and Le Barbanchon, Rathelot, and Roulet (2020).

[5]See also Diamond (2016); Giannone (2017); Caliendo, Opromolla, Parro, and Sforza (2017); Desmet, Nagy, and Rossi-Hansberg (2018); Hsieh and Moretti (2019); Fajgelbaum and Gaubert (2020).

literature is to focus on a different margin of misallocation (across firms of different productivities) and to show how we can quantify it using a model with labor market frictions and matched employer-employee data.[6] The quantitative spatial frameworks typically allow for a rich spatial heterogeneity, and consider workers that draw a vector of comparative advantages towards regions and/or occupations. Barriers to labor mobility may thus trap workers into a mismatched job, leading to misallocation of talent and aggregate productivity losses.[7] This channel has a very limited role in our framework, which instead focuses on the misallocation of labor across firms with different productivities and across regions with different distributions of firms. In our model, misallocation is not driven by mismatch of talent, but rather by misallocation of inputs, closer to the wedge approach of Hsieh and Klenow (2009) and Restuccia and Rogerson (2013) but generated endogenously by the interaction between labor and spatial frictions.[8]

Methodologically, we extend a wage posting model à la Burdett and Mortensen (1998) to incorporate a spatial structure. Our framework is most closely related to job ladder models with labor mobility across sectors, such as Meghir, Narita, and Robin (2015), Hoffmann and Shi (2016), and Bradley, Postel-Vinay, and Turon (2017).[9] In contrast to our work, however, these models do not consider switching costs between sectors, and therefore two workers with the same current value of employment accept the same job offers regardless of their current sector. In our setup, instead, workers' acceptance decisions not only depend on their current value but also on their current location: two workers with the same value may decide differently if they are in different locations. The existing frameworks cannot be applied to our research question since to do so we would need to assume that there is no cost of moving between locations.

At a conceptual level, our work also contributes to the fast-growing literature on local monopsony power (e.g., Berger, Herkenhoff, and Mongey (2022), Yeh, Macaluso, and Hershbein (2022)), and in particular to work that links labor market power to spatial frictions such as commuting costs (Caldwell and Danieli (2021), Datta (2022)).[10] Relative to this work, our paper analyzes how changes to spatial frictions affect monopsony power and endogenously reallocate workers within local labor markets.[11] The reallocation of workers towards higher productivity

[6]These type of data have, to the best of our knowledge, not yet been used by this literature. One way to see our contribution is that we bring to the quantitative literature on spatial frictions insights from the large labor literature that has estimated models with on-the-job search in matched employer-employee data, e.g., Lise, Meghir, and Robin (2016); Bagger and Lentz (2019); Bonhomme, Lamadon, and Manresa (2019).

[7]See Nakamura, Sigurdsson, and Steinsson (2022) for causal evidence supporting this mechanism.

[8]Krueger and Pischke (1995), Hunt (2001, 2006), Fuchs-Schündeln, Krueger, and Sommer (2010), Uhlig (2006, 2008), Dauth, Lee, Findeisen, and Porzio (2021), and Boeri, Ichino, Moretti, and Posch (2021) focus on understanding the large wage and productivity gaps in the specific German context. We do not seek to provide a comprehensive explanation of the East-West gap in Germany. In particular, we estimate the productivity gap between East and West Germany in our model and take it as given.

[9]A large literature has estimated versions of Burdett and Mortensen (1998) models. Examples are Van Den Berg and Ridder (1998); Bontemps, Robin, and Van den Berg (2000); Burdett and Coles (2003); Manning (2013); Burdett, Carrillo-Tudela, and Coles (2020); Moser and Engbom (2021).

[10]See also Manning (2013); Manning and Petrongolo (2017); Hirsch, Jahn, Manning, and Oberfichtner (2022).

[11]Similar to us, Galenianos, Kircher, and Virag (2011) and Bachmann, Bayer, Stüber, and Wellschmied (2021)

firms and the exit of unproductive ones in our model is similar in spirit to the within-industry reallocation in international trade when trade barriers are removed (Pavcnik (2002), Melitz (2003)). However, reallocation in our framework comes from a very different mechanism: competition for workers in the labor market, rather than for customers in the output market.

Finally, there is a large literature that studies the size of spatial frictions and the gains from migration either in partial equilibrium (e.g., Kennan and Walker (2011); Baum-Snow and Pavan (2012)) or by estimating reduced form specifications in panel data (Hicks, Kleemans, Li, and Miguel (2017), Lagakos, Marshall, Mobarak, Vernot, and Waugh (2020)).[12] Closest to our work, Schmutz and Sidibé (2018) build a framework in which workers receive job offers both from their current location and from other locations, and estimate the size of spatial search frictions compared to relocation costs.[13] Relative to these papers, we build a general equilibrium framework that provides a structural interpretation to the reduced form evidence and that can be used to study the aggregate impact of spatial frictions. We show that removing spatial frictions can entail large equilibrium effects.

Our paper proceeds as follows. In Section 2 we describe our data, and Section 3 documents stylized facts on the German labor market. Section 4 introduces the model, which we estimate in Section 5 and use to quantify the aggregate and distributional effects of spatial frictions in Section 6. Section 7 concludes.

2 Data

We use two main datasets provided by the German Federal Employment Agency (BA) to document a set of stylized facts that motivate our analysis: i) the Establishment History Panel (BHP) and ii) the longitudinal version of the Linked Employer-Employee Dataset (LIAB).

The BHP is a panel containing a 50% random sample of all establishments in Germany with at least one employee liable to social security on June 30th of a given year. The data are based on social security filings and exclude government employees and the self-employed. Each establishment in the BHP is defined as a company's unit operating in a distinct county and industry.[14] For simplicity, we will refer to these units as "firms". For each such firm in each year, the dataset contains information on location, average wages, the number of employees, and employee characteristics (education, age, gender).

The LIAB data contain records for more than 1.9 million individuals drawn from the In-

emphasize how firms' monopsony power reduces employment at highly productive firms; however, these papers do not analyze the role of spatial frictions in generating local monopsony power.

[12]See also Combes, Duranton, and Gobillon (2008); Roca and Puga (2017); Alvarez (2020).

[13]See also Amior (2019).

[14]Since several plants of the same company may operate in the same county and industry, the establishments in the BHP do not always correspond to economic units such as a plant (Hethey-Maier and Schmieder (2013)).

tegrated Employment Biographies (IEB) of the IAB, which cover all individuals that were employed subject to social security or received social security benefits. These data are linked to information about the firms at which these individuals work from the BHP. For each individual in the sample, the data provide the entire employment history for the period 1993-2014, including unemployment periods as long as the individual received unemployment benefits. Each observation is an employment or unemployment spell, with exact beginning and end dates within a given year.[15] A new spell is recorded each time an individual's employment status changes, for example due to a change in job, wage, or employment status. For individuals that do not change employment status, one spell is recorded for the entire year.

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

We use three additional datasets. First, we obtain information on cost of living differences across German counties from the Federal Institute for Building, Urban Affairs and Spatial Development (BBSR (2009)), which we will use to construct real wages.[16] Second, we supplement our main analysis with annual survey data from the German Socio-Economic Panel (SOEP) to examine additional demographic characteristics and to corroborate some of our main findings. Finally, we use information on firms' profit shares from the ORBIS database by Bureau van Dijk for the model's estimation.

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

[15]We use the term unemployment spell to refer to the period in which an individual is receiving unemployment benefits. After the expiration of the benefits, individuals are not in our dataset until they are employed again.

[16]The data cover about two thirds of the consumption basket, including housing rents, food, durables, holidays, and utilities. We provide further information on the data in Appendix A and provide a map of county-level price levels. East Germany has a 7% lower population-weighted average price level.

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

3 Motivating Facts

To motivate our model and the relevance of our setting, we document three sets of facts on: (i) the distribution of firm wages within and between regions; (ii) wage gains of job-to-job movers within and between regions; (iii) workers' job flows.

3.1 Significant Wage Heterogeneity Between and Within Regions

We first study firm wages and show that there is significant heterogeneity in wages both across regions and across firms within regions.

Figure 1a plots the average real daily wage in each county in the period 2009-2014 from the BHP. What stands out from the figure is the large real wage difference between East and West. To examine whether this East-West wage gap is due to observables, we run firm-level regressions of the form[17]

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

where $\bar{w}_{jt}$ is the average real wage paid by firm j in year t, $\mathbb{I}_{j,East}$ is a dummy for whether firm j is located in the East, X_{jt} is a vector of controls, and δ_t are time fixed effects. We find an East-West wage gap of $\gamma = -.2609$ (s.e. .0074) without controls. Controlling for worker gender, education, and age, firm size, and industry lowers the wage gap to $\gamma = -.2052$ (s.e. .0027), but about 80% of the real wage gap remains unexplained.

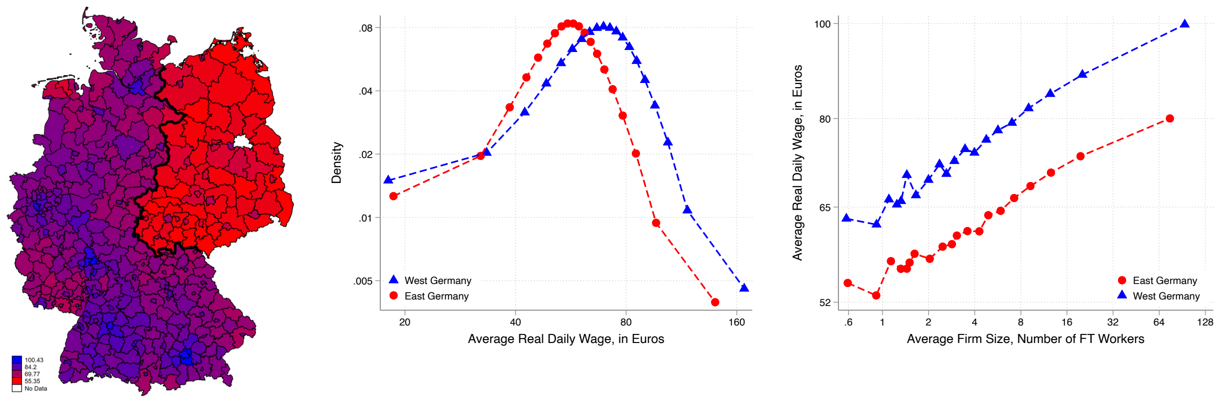
While the wage gap between East and West Germany is striking, we next show that there is even larger wage heterogeneity between firms within each region. Figure 1b plots PDFs of firms' average real wage from the BHP separately for both East and West Germany. We residualize log real wages by regressing them on year dummies and 3-digit industry dummies to remove across industry variation. The figure shows that the wage gap between the lowest- and highest-paying firms in each region exceeds the average wage gap between East and West.[18]

[17] Recall that we refer to establishment units as "firms".

[18] In Supplemental Appendix K, available on the authors' websites, we drill more deeply into this pattern and show that there is similarly large wage dispersion across firms even within the same county. Hence the large dispersion is not just reflecting cross-county differences, consistent with the limited cross-county wage dispersion shown in Figure 1a.

Figure 1: Real Wages Between and Within Regions

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



Source: BHP and authors' calculations. Notes: The left figure shows real daily wages in each county, expressed in 2007 euros valued in Bonn, the former capital of West Germany, and using county-specific prices. Former East-West border is drawn in black for clarification. We exclude Berlin since we cannot assign it unambiguously to "East" or "West". The middle panel plots the density of wages across firms separately for East and West Germany for the period 2009-2014. Wages are residualized by regressing the log real wage on 3-digit industry dummies and time dummies, for East and West Germany separately. We generate the cleaned wage as the residuals from this regression plus the mean of the log wage in the given region and transform these log wages back into levels. We then find the twentiles of the residualized wage distribution, compute the average wage within each twentile, and transform it into a density. While all firms are weighted equally, only a very small share of overall employment is at the lowest wage firms. The right panel plots the average number of full-time workers for each twentile of the firm size distribution against the average real daily wage of firms in the twentile, for both East and West Germany, where wages and size are residualized using the same procedure as before.

Figure 1c further plots the average firm size against the firms' average real wage for twentiles of the firm size distribution. Wage and size are residualized by year and industry dummies as before. Average real wages increase significantly with firm size in both regions, suggesting a job ladder. Additionally, East German firms pay a lower real wage than West German ones for each firm size, suggesting the presence of frictions that shield East German firms from West German competition and allow them to reach a larger size at the same wage level.

In Supplemental Appendix K[19], we show details of regression (1) and provide additional empirical results: (i) the between-region wage gap is persistent over time and similar for all industries; (ii) there are limited differences in observables between East and West German workers; (iii) there are no clearly delineated regional differences in tax rates.

3.2 Large Wage Gains of Movers Across and Within Regions

We next focus on wage gains of movers and show that workers obtain large gains when migrating, especially if moving away from their home region. However, each move across regions is also a move across firms, and we show that workers also experience sizable wage gains for any job-to-job move, even within region.

We analyze workers' wage dynamics around the time of a job-to-job move by running a

[19] This Supplemental Appendix is not meant for publication and includes additional material. It is available on the authors' websites.

standard system of local projections, consisting of one regression for each time period $\tau \in \{t-3, ..., t-1, t+1, ..., t+5\}$ around t:[20]

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

where $w_{i\tau}$ is an individual's weighted average wage across all employment spells in year τ, where we use each spell's length as its weight. We define a job-to-job move as a job switch between two firms without an intermittent unemployment spell. The variable $\Delta \log(w_{i\tau})$ is the log change of this average wage between year τ and the previous year except for $t+1$, where it is the difference with respect to $t-1$. We drop wages from the year of the move to avoid contaminating our results by other types of payments in the year of the move.[21]

The variable d^s_{it} is a dummy for a job switch of type $s \in \mathbb{S}$, where $\mathbb{S}$ is the set of the six possible types of moves: i) from East to West via migration or ii) commuting; iii) from West to East via migration or iv) commuting; v) within-East, and vi) within-West. We distinguish between migration and commuting for moves between East and West Germany because we expect that commuters to a new job are paid a smaller wage premium than workers that also have to move their residence. We classify job-to-job movers between East and West Germany as migrants if they report a different county of residence in the year of the move from the previous year, and define all other moves between East and West as commuting.[22]

The variable $\mathbb{I}^{East}_i$ is a dummy for whether an individual's birth region is East Germany. Since our social security data do not contain information on birth location, we classify individuals as East (West) German if at the first time they appear in our entire dataset since 1993, either employed or unemployed, they are in the East (West). Appendix A provides additional details. Our measure is imperfect, since some individuals migrated between the reunification and 1993. In Appendix C, we use survey data from the SOEP, which include individuals' actual birth location, to show that our measure properly classifies individuals into the region in which they were born in more than 90% of the cases. For this reason, we will interpret workers' home region also as their birth region going forward, and refer to individuals whose home is East as East-born.[23]

The controls X_{it} include dummies for the current work region, home region, and their inter-

[20] We pool together all the data for time periods t from 2004 to 2014 thus creating an unbalanced panel. In general, working with an unbalanced panel could be problematic. In our application, we are less concerned because: i) we do not observe post-trends; and ii) we are mostly interested in the wage growth on impact.

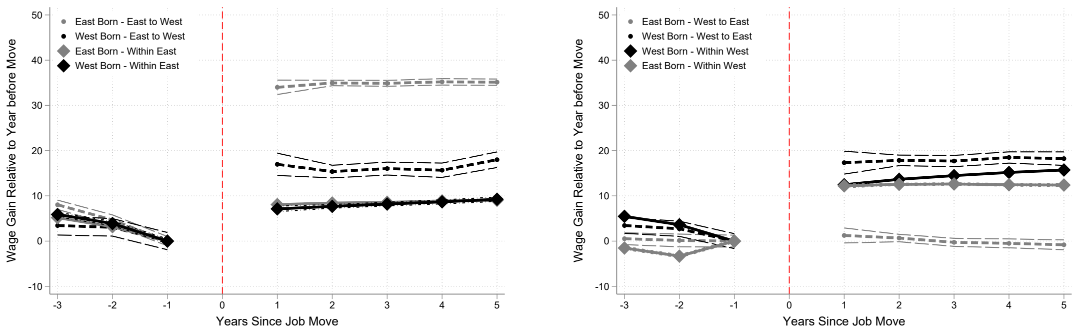
[21] The results are similar if we include year t, see Supplemental Appendix L.

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

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

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

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



Source: LIAB and authors' calculations. Notes: The figure is constructed by taking the point estimates for different sets of coefficients $\beta^{West}_{s,\tau}$ and $\beta^{East}_{s,\tau}$ from the regressions (2) for $\tau \in \{t-3, ..., t-1, t+1, t+5\}$. We then sum up the coefficients starting at $\tau = -3$ to obtain for each period τ the sum $\sum_{u=-3}^{\tau} \beta^{i}_{s,u}$, where $i \in$ {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 $\beta^{East}_{WW,\tau}$.

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

The dashed lines in Figure 2a plot the estimated wage gains for East-to-West migration by East Germans (gray) and West Germans (black) – i.e. the predicted wage from the relevant coefficients $\beta^{West}_{s,\tau}$ and $\beta^{East}_{s,\tau}$, translated into levels, and normalized around the wage level prior to the year of the migration. East-born movers to the West receive on average almost a 35% real wage increase relative to their average within-firm wage growth, which is almost double the wage gain obtained by West-born workers making the same move. The dashed lines in Figure 2b present the analogous wage gains for West-to-East migration. Moves to the East are associated with sizable wage gains for West-born workers and almost no effect for East-born ones. The figures highlight that cross-region movers obtain significant wage increases, in particular those moving out of their home region, suggesting that workers need to be compensated to leave their home region (home bias). Moreover, average wage gains for moves to the East tend to be smaller than for moves to the West, consistent with the lower average wage level in the East, and suggesting the presence of large gains from regional integration.

The solid lines with diamonds plot instead the estimated wage gains for within-region job-to-job switches from regression (2) in East Germany (left panel) and in the West (right). Workers experience wage gains of around 10% for any job-to-job move, even within-region, consistent with the notion that they are climbing a job ladder in the presence of labor market frictions.

These observational returns from migration and job-to-job moves should not be interpreted as causal effects. Movers are selected: they are the ones that received sufficiently appealing job offers. Nonetheless, these large wage gains highlight the importance of labor mobility, both within and between regions, for aggregate productivity and they will offer relevant empirical targets to which our model is going to provide a structural interpretation.

In Supplemental Appendix L, we list the full estimates from specification (2), and show that our results are robust to alternative definitions of job-to-job switches and migration.

3.3 Distorted Job Ladder

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

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

$$s^h_{o,d} = \frac{\sum_t n^h_{o,d,t}}{\sum_t \sum_{d \in \mathbb{D}} n^h_{o,d,t}}$$

where $\mathbb{D}$ is the set of all the 402 counties in East and West Germany.[24] We use these shares to fit the gravity equation

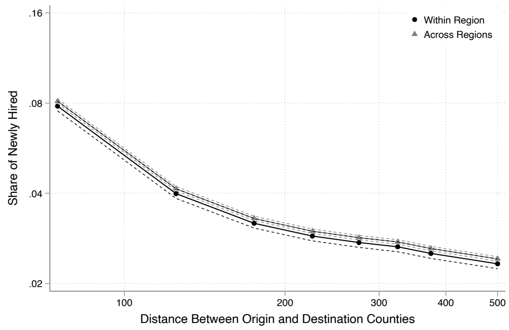
$$\log s^h_{o,d} = \delta^h_o + \gamma^h_d + \sum_{x \in \mathbb{X}} \phi_x D_{x,o,d} + \rho \mathbb{I}_{R(o) \neq R(d)} + \epsilon^h_{o,d}, \tag{3}$$

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

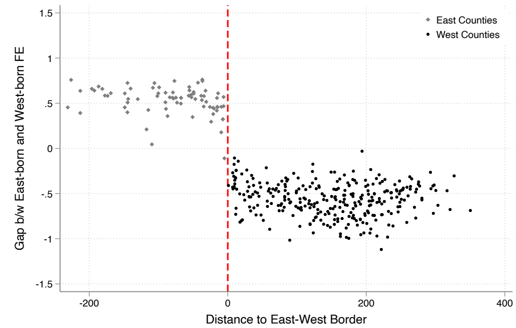
[24] We observe at least one job-to-job flow in some year for 75,937 out of the 160,801 possible origin-destination pairs. When we include also job switches with an intermittent unemployment spell – in Supplemental Appendix M – we have 95,275.

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

(a) Geography



(b) Identity: Destination FE



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

Figure 3a plots the estimated distance coefficients ϕ_x (black line), which we re-normalize into interpretable shares of switchers.[25] Workers move mostly locally, and job switches become less likely for counties that are further apart. The gray line plots the same results for flows between East and West Germany (the coefficients $\hat{\phi}_x + \hat{\rho}$), taking the origin and destination effects as constant. The lines are almost on top of each other. Thus, conditional on distance and fixed effects, we do not find a role for geographical barriers at the East-West border.

Figure 3b shows that there is strong home bias. For each county, we compute the difference between the destination fixed effect for East- and West-born workers, $\gamma_d^{East} - \gamma_d^{West}$. We then plot these differences against each county's distance to the East-West border, defined so that East counties have negative distance.[26] The figure shows that East individuals have significantly higher destination fixed effects for the East, indicating that they are relatively more likely to move to counties in the East than West workers regardless of their current location. Conversely, East-born workers are less likely to move to counties in the West. Supplemental Appendix M provides additional robustness checks for different sub-groups of the population and for different definitions of cross-border mobility.

Despite the strong effects of distance and home bias on worker mobility, the labor markets of East and West Germany are, in fact, tightly connected. Table 1 shows that on average 1% of all employed West and East Germans switch jobs within-region in an average month (row

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

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

Table 1: Summary Statistics on Mobility

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

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

1). For East Germans, the job-to-job transition rate across regions is about one twentieth as high as the transition rate within region (row 2). Row 3 illustrates that 4.6% of West-born and 23.9% of East-born in our sample have ever had a full-time job in the other region over the entire period since 1993. However, between one third and one half of the workers taking a job in the other region return to a job at home, after spending on average only 2-3 years away (rows 4-5).[27] Overall, workers climb a country-wide job ladder, but this ladder is distorted by spatial frictions which lead workers to change jobs mostly locally and to frequently return home. The substantial return migration implies that the gains obtained from cross-region migration may be short-lived if workers, when returning home, move to relatively low productivity firms. This possibility highlights the importance of studying worker allocation to firms both within and between regions.

In Appendix B we present additional statistics on movers and show that the share of workers away from their home region has been relatively stable over the recent period.[28]

4 Model

We now develop a model to quantify how spatial barriers and labor market frictions jointly affect worker mobility across space and firms. Our framework embeds the on-the-job search model of Burdett and Mortensen (1998) into a multi-region economy inhabited by heterogeneous firms and workers, subject to different types of spatial frictions commonly used in the literature: moving costs, home preferences, spatial search frictions, and regional comparative advantages. The model's ingredients are tied to the empirical facts shown in the previous section: first, the

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

[28] This fact, together with the stable wage gap, motivates our analysis in steady state below.

wage dispersion and wage gains within-region call for a model with heterogeneous firms and labor market frictions. Second, the spatial wage gaps and the asymmetries in wage gains and job flows necessitate a model with mobility costs and home bias. Third, the presence of repeated moves across East and West suggests a framework in which individuals draw (infrequently) jobs from different regions.

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

4.1 Environment

Let time be continuous and all agents discount future income at rate r. There are $\mathbb{J} = \{1, ..., J\}$ sites, which we refer to as *locations*.[29] The economy is inhabited by a continuum of workers of types $i \in \mathbb{I}\{1, .., I\}$ with mass $\bar{D}^i$, where $\sum_{i \in \mathbb{I}} \bar{D}^i = 1$. Throughout the text, we will use superscripts for worker types and subscripts for locations. Workers of type i have a preference parameter τ_j^i for being at location j, and consume both a tradable and a local good, such as housing. Their utility is $\mathcal{U}_j^i = \tau_j^i c^\eta h^{1-\eta}$, where c and h are the amounts of tradable good and local good, respectively. A worker of type i produces θ_j^i units of output per time unit in location j. Hence if this worker is employed at wage rate w per efficiency unit, she earns an income of $w\theta_j^i$. Worker i's indirect utility from receiving wage rate w in location j is then $\mathcal{V}_j^i = w\theta_j^i \tau_j^i / P_j$, where $P_j = (P_c)^\eta (P_{h,j})^{1-\eta}$ is the location's price level, P_c is the price of the tradable good, and $P_{h,j}$ the price level of the local good in location j.[30] We normalize $P_c = 1$.

Workers and firms operate in a frictional labor market. We define by e_j^i and u_j^i the mass of employed and unemployed workers of type i in location j, respectively. We introduce spatial search frictions that make it easier for workers to find job opportunities locally, building on a recent literature which uses job application data to show that workers' number of applications declines sharply with the distance of the vacancy (Manning and Petrongolo (2017); Le Barbanchon, Rathelot, and Roulet (2020)).[31] Specifically, workers of type i currently in location j must spend search effort s_x to send $a_{jx}^i(s_x) = z_{jx}^i s_x$ job applications towards location x, where z_{jx}^i is the worker's relative search efficiency, which depends on the worker's current and destination locations (j, x). Search efficiency also depends on the worker's type i. For example, it may be easier for workers to find open positions in their home location due to reliance on social networks

[29] We introduce the term "locations" to differentiate it from the two regions in the empirical section. We will estimate the model below with four locations that are sub-units of the East and West German regions.

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

[31] Schmutz and Sidibé (2018) also incorporate spatial search frictions into their model to capture the lack of migration between areas with very different unemployment rates. In Bilal (2021), unemployed workers search for jobs only in the local labor market.

or referrals (as in, e.g., Galenianos (2013)). Search effort is subject to a cost, to be paid for each location x in which the worker files applications, given by $\psi(s_x) = \frac{s_x^{1+\epsilon}}{1+\epsilon}$ for employed workers. Unemployed workers face a cost $\psi_u(s_x) = \nu^{-\epsilon}\frac{s_x^{1+\epsilon}}{1+\epsilon}$, where $\nu \geq 1$ modulates a potential difference in search intensity between employed and unemployed workers along the lines of Moscarini and Postel-Vinay (2016).

On the firm side, there is a mass M_j of firms exogenously assigned to locations $j \in \mathbb{J}$, with $\sum_{j\in\mathbb{J}} M_j = 1$. Within each location, firms are distributed over labor productivity p according to density function $\frac{\gamma_j(p)}{M_j}$ with support in a location-specific closed set $[\underline{p}_j, \bar{p}_j] \subseteq \mathbb{R}^+$.[32] Each firm p in location j decides how many vacancies $v_j(p)$ to post, subject to a vacancy cost $\xi_j(v)$, and what wage rate $w_j(p)$ to offer, determining the endogenous distributions of wage offers $\{F_j\}_{j\in\mathbb{J}}$. Firms cannot discriminate between worker types, hence they must offer identical wages per efficiency unit to all their workers. Also, firms cannot change their locations.[33]

Matches in location j are created as a function of the total mass of applications filed by workers, $\bar{a}_j$, and vacancies posted by firms, $\bar{v}_j$, according to a matching function $M(\bar{a}_j, \bar{v}_j) = \bar{a}_j^{\chi}\bar{v}_j^{1-\chi}$ as in Diamond-Mortensen-Pissarides models (e.g., Pissarides (2000)). We define market tightness in location j as $\vartheta_j \equiv \frac{\bar{v}_j}{\bar{a}_j}$. Thus, the rate at which a vacancy is filled is $\vartheta_j^{-\chi}$, and the rate at which an application is accepted and becomes a job is $\vartheta_j^{1-\chi}$. Offers are randomly drawn from the endogenous wage offer distributions $\{F_j\}_{j\in\mathbb{J}}$.

Upon receiving an offer from location x, workers draw idiosyncratic preference shocks for locations x and j and decide whether to accept or decline the offer. Movers between j and x incur a utility cost κ_{jx}^i that captures any monetary and non-monetary one-time cost associated with the move across locations, similar to Caliendo, Dvorkin, and Parro (2019). Workers separate exogenously into unemployment at location-type-specific rate δ_j^i and receive an unemployment benefit rate equal to b_j^i per efficiency unit when unemployed. They also always have the possibility to quit and become unemployed, keeping their draw of the preference shocks.

We denote by l_j^i the measure of workers of type i employed per vacancy of a firm, and thus $\sum_{i\in\mathbb{I}} \theta_j^i l_j^i$ is the measure of efficiency units of labor used by one vacancy. Vacancies can produce any combination of the two goods according to the production functions $c = pn_c$ and $h = (pn_h)^{1-\alpha}k^{\alpha}$, where $0 < \alpha(1-\eta) < 1$, and n_c and n_h are the efficiency units of labor per vacancy used in the production of the two goods, which satisfy $n_c + n_h = \sum_{i\in\mathbb{I}} \theta_j^i l_j^i$. The term k is a factor that is in fixed supply, such as land, with aggregate supply in location j of K_j and equilibrium price ρ_j. Firms decide how to allocate labor across the production of the two

[32] Thus, $\gamma_j(p)$ will integrate to the mass of firms in location j, M_j. This definition will simplify notation below.

[33] This assumption is motivated by the fact that, as mentioned, our data is at the establishment level, and thus we cannot see firms relocating or deciding where to open establishments. The model, nonetheless, could easily be adapted to allow entrepreneurs to make a location choice. Note that we allow firms to change their size by changing their number of vacancies, and to effectively enter or exit by going from zero to positive vacancies or vice versa.

goods, taking prices in the output market as given.

In our model, firms compete for all worker types in one unified labor market. That seems an adequate description of the German labor market since we will define worker types based on their home region below, and firms cannot explicitly hire only West Germans, for example. Previous work with heterogeneous types (e.g. Moser and Engbom (2021)) assumes that the labor market is segmented by type. In our framework, each firm p located in j posts a single wage rate $w_j(p)$, which determines the composition of worker types it attracts.

We next describe the equilibrium in the goods market, which pins down local price levels. We then turn to the workers' and firms' optimization problems and the labor market equilibrium.

Goods Market. Consider a firm that has hired $n_j(w) \equiv \sum_{i\in\mathbb{I}} \theta_j^i l_j^i(w)$ efficiency units of labor per vacancy by posting wage w. The firm's remaining problem is

$$\hat{\pi}_j(w) = \max_{n_h,n_c,k} pn_c + P_{h,j}\left(pn_h\right)^{1-\alpha} k^{\alpha} - \rho_j k \tag{4}$$

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

$$\frac{P_j}{P_x} = \left(\frac{P_jY_j}{P_xY_x}\right)^{\alpha(1-\eta)} \left(\frac{K_j}{K_x}\right)^{-\alpha(1-\eta)}, \tag{5}$$

where P_jY_j is the nominal output of location j. If more labor moves to location j, increasing output Y_j relative to Y_x, then the relative local price index P_j/P_x rises, due to the presence of the fixed factor. As a result, there is local congestion as typical in spatial models (e.g. Allen and Arkolakis (2014)). Substituting in the optimal choices and equilibrium price, we can simplify $\hat{\pi}(w)$ to

$$\hat{\pi}_j(w) = pn_j(w) = p\sum_{i\in\mathbb{I}} \theta_j^i l_j^i(w). \tag{6}$$

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

Workers. Workers choose search effort for each location x, file applications, and randomly and infrequently receive offers from firms. Workers accept an offer if it provides higher expected value than the current one. As is known, this class of models yields a recursive representation (e.g., Burdett and Mortensen (1998)).

The acceptance decision of an employed worker of type i earning wage w in location j, given an offer from a firm in location x paying wage w', solves

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

where $W_j^i(w)$ is the value of employment at wage w in location j, $W_x^i(w')$ is the value of employment in location x at wage w', and $\kappa_{jx}^i = 0$ if $j = x$. The terms ε_j and ε_x are idiosyncratic shocks drawn from a type-I extreme value distribution with zero mean and standard deviation σ, which capture shocks to workers' preferences for being in a specific firm and location.[34] These shocks simplify the model characterization and computation. We assume that workers can always separate into unemployment keeping the same shocks, which allows us to pin down the lower bound for wages in each location, as in the original formulation of Burdett and Mortensen (1998).

Given the properties of the type-I extreme value distribution, the probability that an employed worker of type i accepts an offer is given by

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

and the expected value of an offer is

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

The problem for an unemployed worker is identical, but replacing $W_j^i(w)$ with the value of unemployment U_j^i.[35] We use notation $\mu_{jx}^{U,i}\left(b_j^i, w'\right)$ to refer to the probability that an unemployed worker accepts an offer w', and use $V_{jx}^{U,i}\left(b_j^i, w'\right)$ for the expected value of the offer.

The discounted expected value of employment $W_j^i(w)$ of a worker i earning wage w in location j consists of the real flow value of employment, $w\theta_j^i\tau_j^i/P_j$, a continuation value for drawing new job offers from location x at rate $a_{jx}^i(s_x)\vartheta_x^{1-\chi}$, which is a function of the optimal search effort s_x, and a continuation value for separating into unemployment at rate δ_j^i:

$$\begin{aligned} rW_j^i(w) &= \frac{w\theta_j^i\tau_j^i}{P_j} + \max_{\{s_x\}_{x\in\mathbb{J}}} \sum_{x\in\mathbb{J}} \left(a_{jx}^i(s_x)\vartheta_x^{1-\chi}\left[\int V_{jx}^{E,i}(w, w')\,dF_x(w') - W_j^i(w)\right] - \psi(s_x)\right) \\ &+ \delta_j^i\left[U_j^i - W_j^i(w)\right]. \end{aligned} \tag{7}$$

Similarly, the unemployment value is:[36]

$$rU_j^i = \frac{b_j^i\theta_j^i\tau_j^i}{P_j} + \max_{\{s_x\}_{x\in\mathbb{J}}} \sum_{x\in\mathbb{J}} \left(a_{jx}^i(s_x)\vartheta_x^{1-\chi}\left[\int V_{jx}^{U,i}\left(b_j^i, w'\right)dF_x(w') - U_j^i\right] - \psi_u(s_x)\right). \tag{8}$$

[34] This problem is isomorphic to an alternative formulation in which workers only draw a shock for the value of accepting the offer, where that shock follows a logistic distribution.

[35] We show these equations in Appendix D.2.

[36] Appendix D.2 shows expressions for (7) and (8) once we solve out for optimal search effort.

We denote by $s_{jx}^{E,i}(w)$ and $s_{jx}^{U,i}(b)$ the optimal search efforts of an employed worker with wage w and an unemployed worker with benefit b, respectively, that are currently in location j and searching in location x. We define by $a_{jx}^{E,i}(w)$ and $a_{jx}^{U,i}(b)$ the associated mass of applications. The total mass of applications filed for jobs in location j by workers of type i is then

$$\bar{a}_j^i \equiv \sum_{x \in \mathbb{J}} \left[\int a_{xj}^{E,i}(w)\, dE_x^i(w) + a_{xj}^{U,i}(b)\, u_x^i \right], \tag{9}$$

where $E_j^i(w)$ is the mass of employed workers of type i at firms in location j receiving at most w, with $E_j^i(w(\bar{p}_j)) = e_j^i$. The total number of applications by location is $\bar{a}_j \equiv \sum_{i \in \mathbb{I}} \bar{a}_j^i$.

Firms. Since the firms' production functions are linear, the firm-level problem of posting vacancies and choosing wages can be solved separately. Employers choose the wage rate that maximizes their steady state profits for each vacancy

$$\pi_j(p) = \max_w (p - w) \sum_{i \in \mathbb{I}} \theta_j^i l_j^i(w), \tag{10}$$

where $p \sum_{i \in \mathbb{I}} \theta_j^i l_j^i(w)$ are the net revenues from the goods market from (6).

Firms choose the number of vacancies to maximize total profits

$$\varrho_j(p) = \max_v \pi_j(p)\, \vartheta_j^{-\chi} v - \xi_j(v), \tag{11}$$

where $\pi_j(p)$ are the maximized profits per vacancy from (10). The overall size of a firm p in location j is given by $l_j(w_j(p))v_j(p)$, where $w_j(p)$ is the profit-maximizing wage.

Firms' vacancy posting and wage policies give the total mass of offers posted in each location and the endogenous offer distribution

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

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

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

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

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

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

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

The second term in (14) is the separation rate, where

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

which consists of the exogenous separation rate into unemployment plus the rate at which workers receive and accept offers from other firms – i.e. poaching within and across locations. As usual, we can use the law of motion (14) to solve for the steady state mass of workers per vacancy

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

and zero otherwise.

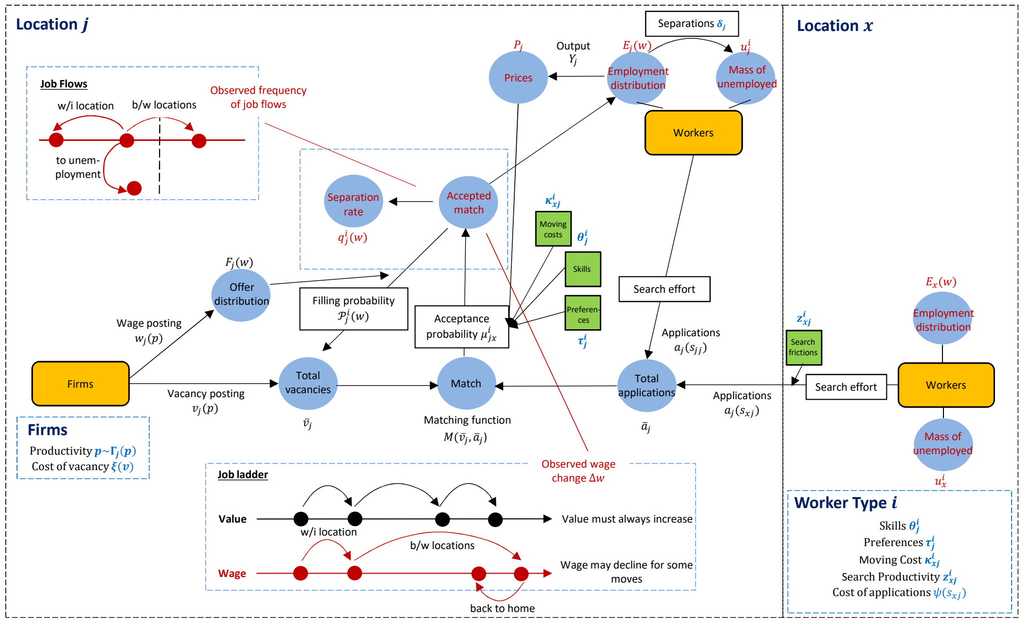
The mass of employed workers i in location j at firms paying at most w satisfies

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

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

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

Figure 4: Illustration of the Model



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

Figure 4 illustrates the main building blocks of our model and how they fit together. Yellow boxes denote the model's agents, blue circles endogenous objects, and green squares spatial frictions. We use red text for observable objects and black text for unobservables. The right-hand side of the diagram shows employed and unemployed workers in some location x. These workers exert search effort to post applications to some location j, subject to spatial search frictions. Workers already in location j also exert search effort but do not face the same spatial frictions since they search within-location. The left-hand side of the diagram shows the firm side. Heterogeneous firms post vacancies as well as wages, summarized by the wage offer distribution. Vacancies and applications meet in a frictional labor market, where the meeting probability depends on the ratio of total vacancies and applications, i.e., tightness. Given a match, workers' acceptance probability depends on the wage offered as well as the worker's moving costs, preferences, skills, and the price level. We illustrate the worker's acceptance decision in the dashed box at the bottom of the diagram. Workers' accept any offer that offers a higher value than their current one. However, workers' wage does not necessarily have to increase, since a wage loss can be compensated for example by a higher location preference. Workers that accept an offer separate from their previous job if they were employed, generating an endogenous separation rate. We illustrate worker flows in the box at the top left. Matches and separations determine the employment distribution and unemployment in location j, which in turn determine output and hence the price level.

4.2 Stationary Equilibrium

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

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

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

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

3. *the arrival rates of offers and wage offer distributions are consistent with aggregate applications, wage policies, and vacancy posting, according to equations (9), (10), and (12);*

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

The model does not admit an analytical solution. Yet, the following proposition shows that the wage policies follow a system of differential equations, facilitating the computation of the model.

Proposition 1. *The J location-specific equilibrium wage functions* $\{w_j(p)\}_{j\in\mathbb{J}}$ *solve a system of differential equations*

$$w_j(p) \quad = \quad w_j\left(\underline{p}_j\right) + \int_{\underline{p}_j}^{p} \frac{\partial w_j(z)}{\partial z}\gamma_j(z)\,dz$$

where, defining $\tilde{x}(p) \equiv x(w(p))$ *for any* x*,*

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

and

$$\tilde{q}_j^i(p) \equiv \delta_j^i + \sum_{x\in\mathbb{J}} \vartheta_x^{1-\chi}\tilde{a}_{jx}^{E,i}(p)\int \tilde{\mu}_{jx}^{E,i}(z,z')\,d\tilde{F}_x(z')$$

$$\tilde{\mathcal{P}}_j^i(p) \equiv \frac{1}{\bar{a}_j^i}\sum_{x\in\mathbb{J}}\left[\int \tilde{a}_{xj}^{E,i}(z')\,\tilde{\mu}_{xj}^{E,i}(z',z)\,d\tilde{E}_x^i(z') + a_{xj}^{U,i}(b)\,\tilde{\mu}_{xj}^{U,i}(b,p)\,u_x^i\right]$$

together with J boundary conditions for $w_j\left(\underline{p}_j\right)$ satisfying

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

Proof. See Appendix D.3. □

Our framework is a generalization of Mortensen (2005). In Appendix D.4, we show that our model collapses to the standard framework if we shut down the spatial heterogeneity and the preference shocks.

5 Estimation

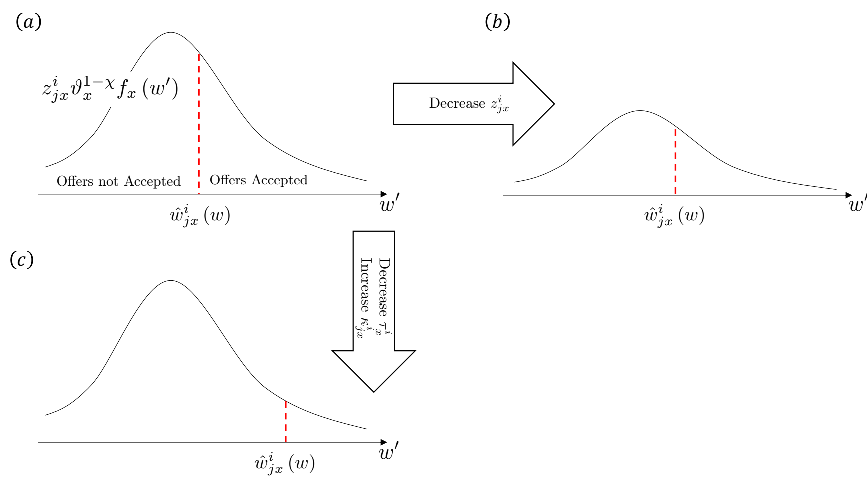
We next estimate the model using the German data described in Section 2.

5.1 Identifying the Spatial Frictions

Estimating the model requires us to separately identify the spatial frictions (κ_{jx}^i, τ_j^i, and z_{jx}^i) from the labor market frictions. Our strategy relies on the insight that labor market frictions mostly affect the allocation of labor within each location, and can therefore be identified from within-location moments, using similar moments as in the standard estimation of Burdett-Mortensen models (see, e.g., Bontemps, Robin, and Van den Berg (2000)). Given the labor market frictions, the spatial frictions can then be inferred from cross-location moments. While all model parameters are jointly identified, we illustrate our identification argument in Figure 5. Each panel shows the mass of job offers with a given wage w' that is generated by a unit of search effort directed towards location x from location j, $z_{jx}^i\vartheta_x^{1-\chi}f_x(w')$.

To simplify the exposition, we assume that $\sigma \to 0$ so that an offer w' from location x is accepted by a worker of type i employed in region j at wage w if and only if $W_x^i(w') - \kappa_{jx}^i \geq W_j^i(w)$. Let $\hat{w}_{jx}^i(w)$ be the cutoff wage offer such that $W_x^i\left(\hat{w}_{jx}^i(w)\right) - \kappa_{jx}^i = W_j^i(w)$. The accepted offers are the ones to the right of $\hat{w}_{jx}^i(w)$, and the mass of job flows per unit of search effort is the integral under the wage offer density to the right of $\hat{w}_{jx}^i(w)$. Going from panel (a) to (b), a decrease in the search efficiency z_{jx}^i reduces the mass of offers received, and hence the

Figure 5: Identifying Spatial Frictions



worker flows from location j to x. However, it does not affect the cutoff $\hat{w}^i_{jx}(w)$, and hence has no effect on average wage gain of workers that accept the offer and move from j to x.

Panel (c) shows the effect of a decline in the worker's preference for location x, τ^i_x, which shifts the acceptance location to the right (a similar argument applies for the moving cost, κ^i_{jx}). A decrease in τ^i_x (or an increase in κ^i_{jx}) raises the 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^i_{jx} and decreases in τ^i_x.

The identification argument illustrates that we need both worker flows and wage gains to separate the effect of the search efficiency from location preferences and moving costs. However, without further restrictions, we cannot separate the moving costs from location preference. We therefore assume that moving costs are identical for all worker types, reflecting for example relocation costs and transaction costs on the housing market. Under that assumption, we can separately identify the location preferences using the differences in wage gains for individuals of different types that make the same migration move, e.g., East versus West Germans that move from East to West.[37]

Discussion of Identifying Assumptions. Our argument is based on two core assumptions of the Burdett and Mortensen (1998) framework: wage posting and random search.

The wage posting protocol implies that firms cannot discriminate based on workers' type or current location. This assumption is supported by recent evidence that shows that the outside option has a limited effect on workers' wages (Jäger, Schoefer, Young, and Zweimüller (2020))

[37] Appendix E.1 provides further details, and Appendix H.3 uses simulations of the model to verify that the identification argument holds in practice.

and that, conditional on the current firm, a worker's previous firm has almost no effect on current wages (Kline, Saggio, and Sølvsten (2019)). Nonetheless, we note that under a different wage setting method larger wage gains for movers between locations could be driven by firms offering wage premia to compensate workers that have to migrate to take a job. In our framework, these premia would be identified as moving costs as long as they are common across workers.

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

5.2 Parametrization and Calibrated Parameters

While the model can be solved for arbitrarily many locations, adding locations reduces the computation speed significantly and increases the number of targeted moments exponentially since we need to match worker flows and wage gains between every pair of locations for every worker type. To keep the estimation time feasible and to limit the number of moments and parameters, we set the number of locations to four, two in the West and two in the East − Northwest ($j = NW$), Southwest ($j = SW$), Northeast ($j = NE$), and Southeast ($j = SE$), and choose four worker types, which are distinguished by their home location.[38] This number of locations and types allows us to distinguish the role of the former East-West border from other spatial frictions between locations. We will continue to refer to East and West Germany overall as "regions".

Functional Forms. We set a unit interval of time to be one month.[39] Firms' log productivity is drawn from a log-normal distribution with equal variance in all locations, Σ, and mean A_j.

[38]This parametrization implies that we need to match $4\times4\times4 = 64$ wage gains and 64 worker flows. Appendix F provides further details on the locations. In robustness checks below, we analyze the effect of increasing the number of locations on our main findings.

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

We normalize $A_{NW}=1$ and refer to A_j as the relative aggregate productivity in location j.

We parametrize the vacancy cost function as $\xi_j(v)=\frac{\xi_{0,j}^{-\xi_1}}{1+\xi_1}v^{1+\xi_1}\bar{\pi}_j(p)$, where $\xi_{0,j}$ and ξ_1 are parameters to be estimated, and $\bar{\pi}_j(p)$ is the average firm profit in location j. This parametrization implies that the equilibrium mass of vacancies posted by a firm with productivity p is $v_j(p)=\xi_{0,j}\left(\frac{\pi_j(p)}{\bar{\pi}_j(p)}\right)^{\frac{1}{\xi_1}}$.[40] We assume that the curvature ξ_1 is constant across locations but allow $\xi_{0,j}$ to be specific to the overall region – i.e. we estimate $\xi_{0,W}$ and $\xi_{0,E}$.

For the unemployment benefit rates b_j^i, we set the reservation wages directly and assume that all worker types have identical reservation wage R_j within each location, where R_j is equal to a fraction ι of the productivity of the lowest productivity firm, $R_j=\iota\underline{p}_j$.[41] Note that due to the spatial frictions, workers' utility differs across types despite equal reservation wages.

Parametrizing Spatial Frictions. We interpret the moving cost κ_{jx}^i as the opportunity cost of foregone wages (Sjaastad (1962)), and assume that it is symmetric and proportional to the average value for each worker: $\kappa_{jx}^i=\hat{\kappa}_{jx}\bar{W}^i$, where $\bar{W}^i=\frac{1}{e^i}\sum_{j\in\mathbb{J}}\int W_j^i(w)\,dE_j^i(w)$ and $e^i\equiv\sum_{j\in\mathbb{J}}e_j^i$.[42] We assume that $\hat{\kappa}_{jx}$ is a function of distance between locations j and x, and, given our identification argument above, identical for all workers,

$$\hat{\kappa}_{jx}=\begin{cases}0 & \text{if } j=x\\ \kappa_0 e^{\kappa_1 dist_{jx}} & \text{if } j\neq x\end{cases}.$$

We specify worker preferences τ_j^i to be the product of three terms:

$$\tau_j^i \quad = \quad \underbrace{\tau_j}_{\text{Amenities}}\underbrace{\left(1-\tau_l\mathbb{I}_{(i\neq j)\cap(r(i)=r(j))}\right)}_{\text{Home Location Bias}}\underbrace{\left(1-\tau_r\mathbb{I}_{r(i)\neq r(j)}\right)}_{\text{Home Region Bias}},$$

where τ_j captures general amenities of location j, τ_l captures a worker's utility cost to live outside of her home location but inside her home region, and τ_r is the cost to live outside the home region, where $r(i)$ maps locations to regions. This specification allows individuals to value

[40] The normalization can be interpreted as capturing the fact that vacancy creation requires work by individuals whose outside option would be to start a firm (getting a productivity draw from the existing distribution). The normalization is without loss of generality in the estimation as it simply changes the estimated values of $\xi_{0,j}$. Instead, in the counterfactuals it limits the relationship between average firm profits and vacancy posting. Our assumption implies that in the counterfactuals the overall amount of posted vacancies is relatively constant, and the results are mostly driven by a shift in the relative vacancy posting across the firm productivity distribution rather than by an aggregate shift in the demand for labor. Since our firm data do not allow us to discipline the total amount of vacancies posted, we prefer to be conservative and to limit the quantitative relevance of this channel.

[41] While R_j is endogenous, setting its value directly is the same as choosing a set of unemployment benefits b_j^i that imply such a reservation wage, hence that solve $U_j^i=W_j^i(R_j)$.

[42] We impose this scaling because if κ_{jx}^i were a constant for all i, then the moving cost would be more binding for East-born workers since these have on average lower wages at any firm, as we show below.

both their home location and their overall home region, i.e., East or West Germany.

We specify the search efficiency z^i_{jx} to be a function of both geography and identity:

$$z^i_{jx} = \begin{cases} (1 - z_{l,1}\mathbb{I}_{i\neq j}) & \text{if } j = x \\ \left(z_0 e^{-z_1 dist_{jx}}\right)\left(1 + z_{l,2}\mathbb{I}_{i=x}\right)\left(1 + z_r \mathbb{I}_{(r(i)=r(x))\cap(i\neq x)}\right) & \text{if } j \neq x \end{cases}.$$

In the first expression, which governs within-location moves, the parameter $z_{l,1}$ captures that workers might be less effective in filing applications when they are away from their home location. In the second expression, which governs across-location moves, the parameters z_0 and z_1 allow workers' search efficiency to decay with distance. The parameters $z_{l,2}$ and z_r allow workers' search efficiency to be relatively higher towards their home location and region.

To reduce the number of parameters to be estimated we make two further assumptions. First, we restrict $A_{NE} = A_{SE}$ since average wages and GDP per capita are similar in the Northeast and the Southeast, see Appendix F. Second, matching this assumption, we assume that local amenities are the same, $\tau_{NE} = \tau_{SE} = \tau_E$. We show below that despite these restrictions, we match well the location-specific moments of the Northeast and Southeast.

Calibrated Parameters. We calibrate eight sets of parameters listed in Table 2. Most of them are straightforward and we describe how we set their values in Appendix G. We focus here on how we set workers' relative productivity, θ^i_j (row 1). We use the fact that due to wage posting and the assumption that firms post the same wage to all workers' types, the model yields a log additive wage equation

$$\log w^i_j(p) \quad = \quad \log \theta^i_j + \log w_j(p).$$

This equation is similar to the specification by Abowd, Kramarz, and Margolis (1999), with the main difference that in our specification θ^i_j is not an individual fixed effect but both individual- and location-specific. This allows for *comparative advantage* when a worker is employed in her home location, i.e., she could have higher productivity there.[43] To estimate this parameter, we run a modified AKM regression

$$\log(w_{it}) = \alpha_i + \psi_{J(i,t)} + \beta\mathbb{I}^{(h_i\neq R(J(i,t)))} + BX_{it} + \epsilon_{it}, \tag{20}$$

where α_i is the worker component of worker i, $\psi_{J(i,t)}$ is the component of the firm j for which worker i works at time t, and $\mathbb{I}^{(h_i\neq R(J(i,t)))}$ is a dummy that is equal to one if worker i with

[43]In practice, we only allow for *regional* comparative advantage. Our main hypothesis is that East Germans might have obsolete skills that cannot easily be transferred to the West German firms which have more advanced technologies.

Table 2: Calibrated Parameters

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

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

home region h_i is currently employed at a firm in the other region.[44] We show in Appendix E.2 that β identifies the comparative advantage of workers in their home region, $\theta_i^{r(i)}$, and implement the estimation in Appendix G.1. We estimate $\beta = 0.019$, indicating a small *negative* comparative advantage towards the home region. 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 compute workers' average skills, θ^i, from the average worker fixed effects α_i. Based on our estimation, the average East German worker's unobserved skills are about 9 percentage points below those of a West German worker.

5.3 Estimation Targets

We are left with 21 parameters that we jointly estimate through simulated method of moments, and target the 305 moments summarized in Table 3. Appendix G.2 includes details on how each moment is computed. We provide a brief rationale on how the targets are chosen.

As described in Section 5.1, targeting the wage gains and job flows (rows 1-4 of Table 3) is key to identify the spatial frictions. In a steady state equilibrium, the job flows are directly tied

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

to the allocation of labor across locations, hence we target those moments as well (rows 5-6). We ask our model to match aggregate measures of economic performance (wages, output per worker, unemployment; rows 8-10) to be consistent with the stark regional gaps.

For the within-location allocation of labor to firms, we target several moments disciplining the way in which the job ladder works: the joint distribution of firm wages and size (rows 11-12); the relationship between firm wages and the separation rates and wage gains of their workers (rows 13-14); and how directed the typical job-to-job moves are, as measured by the standard deviation of the wage gains across workers (rows 15). Finally, we target the firm profitability (row 16) as a natural way to discipline the overall extent of monopsony power in each location.

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

The mapping between model and data is straightforward since we can compute exactly the same objects in both. One small complication is that a sizable share of individuals in our data report to be working in a location different from their residence, while in the model we do not distinguish between migration and commuting. We thus need to decide how to define job flows across locations. As our baseline, we count as cross-location migrants all individuals that change their work location and satisfy either one of these two conditions: i) they update their residence; ii) their new job is further away from their residence than the old one and both jobs are within 200km of their residence (otherwise, we suspect that the residence is simply misreported).[45] In Supplemental Appendix N, we re-estimate our model with a broader and a narrower definition of cross-location moves and show that this mainly affects our estimates of the moving cost, while keeping most results unchanged.

5.4 Identification and Model Fit

We estimate the model using a standard indirect inference approach and provide more details on our estimation algorithm in Appendix H.[46] While all parameters are jointly identified in equilibrium, we next analyze the connection between all parameters and moments via model simulations, and verify that the heuristic identification argument for the spatial frictions holds

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

[46]Figure A5 shows that the model likelihoods are locally single-peaked around each parameter estimate.

Table 3: Targeted Moments

	Moments	N	Source	Model Fit	Key Parameters
(1)	Wage gains w/i locations, by (i,j)	16	Sect G.2.1	Fig 6	Σ, σ
(2)	Wage gains b/w locations, by (i,j,x)	48	Sect G.2.1	Fig 6	κ, τ_j^i, Σ
(3)	Job flows w/i locations, by(i,j)	16	Sect G.2.2	Fig 6	ϵ, ξ_0
(4)	Job flows b/w locations, by (i,j,x)	48	Sect G.2.2	Fig 6	z_{jx}^i, κ
(5)	Employment shares, by (i,j)	16	Sect G.2.3	Fig A7	κ, z_{jj}^i, τ_j, τ_j^i, z_{jx}^i
(6)	Unemployment shares, by (i,j)	16	Sect G.2.4	Fig A7	κ, z_{jj}^i, τ_j, τ_j^i, z_{jx}^i
(7)	Firm component of wages, by (i,j)	15	Sect G.2.5	Fig A7	A_j, τ_j
(8)	Average firm component of wages, by j	3	Sect G.2.6	Fig A7	A_j, τ_j ,z_{jj}^i, τ_j^i
(9)	Relative output per worker, by j	3	Sect G.2.7	Fig A7	A_j, ν
(10)	Unemployment rates, by j	4	Sect G.2.8	Fig A7	ν
(11)	Deciles of firm-size distributions, by j	40	Sect G.2.9	Fig A8	ξ_1
(12)	Slope of wage vs firm size relationship, by j	4	Sect G.2.10	Table A28 and Fig A9	ξ_1 , ι
(13)	Slope of J2J wage gain vs firm wage, by j	4	Sect G.2.11	Table A28 and Fig A9	Σ, σ
(14)	Slope of separation rate vs firm wage, by j	4	Sect G.2.12	Table A28 and Fig A9	ξ_0 , σ, ϵ
(15)	Std of job-job wage gains, by (i,j,x)	64	Sect G.2.13	Table A28 and Fig A10	Σ, ξ_0 , ϵ, ι, σ
(16)	Profit to labor cost ratio, by j	4	Sect G.2.14	Table A28	σ, ξ_1 , ι,ξ_0, τ_j^i

Notes: The table reports the moments used in the estimation. The column titled "N" lists the number of moments in the group. Column "Source" links to the appendix section where the moment is computed, and column "Model fit" lists the table or figure that compares the empirical moment to the model-computed moment. The last column lists the key parameters that are pinned down by each set of moments as explained in Section H.3.

in practice. We then evaluate the model fit.

Identification. We compute the elasticity of each (model generated) moment to each parameter, and provide the Jacobian matrix in Appendix H.3. The last column of Table 3 reports the most important parameters for each moment based on this exercise.[47]

A few comments are in order. First, and importantly, the Jacobian matrix verifies that the heuristic argument made in Section 5.1 holds. The wage gains between regions (row 2 of Table 3) are crucial for the moving costs κ and the preference τ_j^i, while the job flows between regions (row 4) are especially important for the relative search efficiencies z_{jx}^i. The spatial frictions are also crucial for the steady state allocation of employed and unemployed workers (rows 5-6). As expected, the within region wage gains and flows (rows 1 and 3) are, instead, not relevant for the spatial frictions. Instead, large within region wage gains are driven by either a large variance

[47]Since the full Jacobian matrix includes 6,405 (305×21) cells, in our exposition we take averages of the 16 blocks of moments shown in Table 3 and show these averages rather than each moment separately. In the table and graph, we bundle together a few sets of closely related parameters and refer to them jointly as follows: i. the two relative amenities τ_{SW} and τ_E (we refer to them jointly as $\tau_j \equiv \{\tau_{SW}, \tau_E\}$); ii. the two home biases τ_l and τ_r $\left(\tau_j^i \equiv \{\tau_l, \tau_r\}\right)$; iii. the relative search efficiencies between regions z_0, z_1, $z_{l,2}$ and z_r $\left(z_{jx}^i \equiv \{z_0, z_1, z_{l,2}, z_r\}\right)$; iv. the cost of moving κ_0 and κ_1 ($\kappa \equiv \{\kappa_0, \kappa_1\}$); v. the two relative productivities A_{SW} and A_E ($A \equiv \{A_{SW}, A_E\}$); vi. the two costs of vacancy posting $\xi_{0,W}$ and $\xi_{0,E}$ ($\xi_0 \equiv \{\xi_{0,W}, \xi_{0,E}\}$).

of the productivity distribution (Σ), or a low variance of the taste shock (σ) so that workers only accept job offers with an associated wage increase. The job flows are mainly related to the parameters modulating the cost of filing applications (ϵ) and of posting vacancies (ξ_0).

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

Third, the moments that matter most for the efficiency of the job ladder (rows 11-15) are mostly linked to the variance of firm productivity (Σ), the labor market friction parameters ($\xi_0, \xi_1, \epsilon, \sigma$), and the level of the reservation wage relative to firm productivity (ι). This is expected: as already noted, Σ is crucial to determine the variance of wages; ξ_0 and ξ_1 determine the intensity of vacancy posting and how it varies across firms; the cost of search effort ϵ modulates the relationship between workers' search intensity and the value of employment at their current firm; and σ determines how much the job moves are on average directed towards higher wage offers.

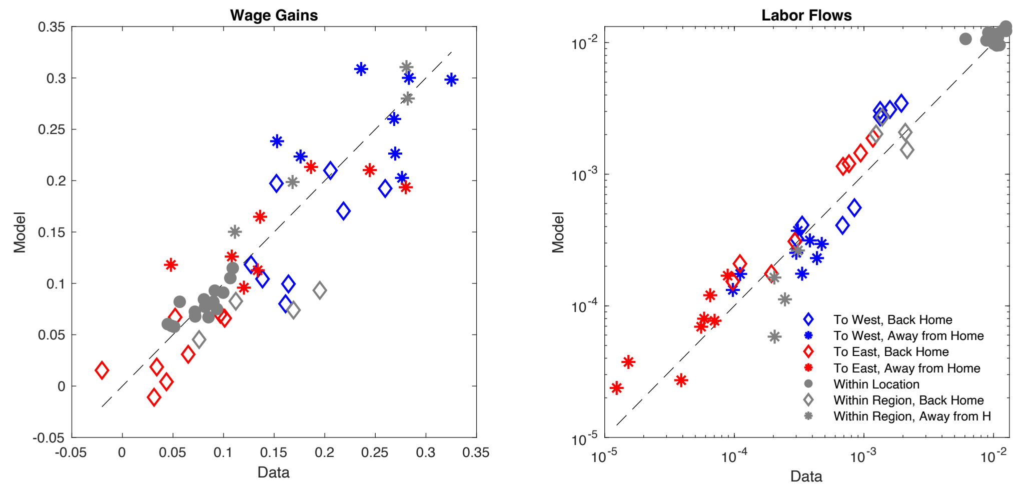
Fourth and last, the firm profitability (row 16) is a function of the labor market friction parameters (σ, ξ_0, ξ_1), as expected since they determine the extent of monopsony power, and the reservation wage ι, which mechanically decreases profitability. The home preference τ_j^i also plays a relevant role: when workers are more attached to a location, firms face effectively less competition from other locations.

Model Fit. The model matches well the key moments that help to identify the spatial frictions. The left panel of Figure 6 plots the wage gains of job-to-job movers in the data against those in the model (from rows 1 and 2 of Table 3).[48] Each dot is for one of the 64 different types of moves by origin-destination-home location, which we color code by direction and type of worker. As in the data, the model generates larger wage gains for moves towards the West (blue symbols), for within-region moves away from the home location (gray stars), and for moves away from the home region, in particular to the West (blue stars). The right panel presents a similar plot for the monthly share of movers in all employed workers (from rows 3 and 4). As in the data, in our model individuals are more likely to move within-location (gray circles) and to move back to their home location and region (diamonds) than away from home (stars).

We discuss the fit of all other moments in Appendix I, and summarize here the main takeaways. The model matches well the steady state distributions of workers and the average GDP, wages, and unemployment rates, consistent with the hypothesis that the German labor market

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

Figure 6: Wage Gains and Frequency of Job Flows



Notes: The left panel shows the average wage gains of different types of job-to-job moves in the data (x-axis) against the average wage gains in the model (y-axis). The right panel shows the frequency of each type of job-to-job move in the data (x-axis) against the frequency in the model (y-axis). Different types of moves are identified by a mix of colors and symbols, listed in the right panel. In total, there are 64 possible types of moves by origin location, destination location, and home location. The data moments are listed in Appendix G.2.1 and G.2.2.

is in a steady state. The model's job ladder mechanism implies that more productive firms offer higher wages and have a lower rate of quits, which allows the model to do a reasonable job in matching the empirical joint distribution of firm wages, sizes, and separation rates, as well as the standard deviations of the wage gains of job movers and firms' profit shares. The model somewhat overestimates the relationship between firm wage and firm size, and generates a smaller standard deviation of wage gains of movers than the data. These results are possibly expected: in the model, wage dispersion across firms is purely generated by labor market frictions, while in the data there may be other sources of wage dispersion that our empirical controls are not capturing.[49]

Overall, the model displays a very good fit considering that we estimate 21 parameters to target 305 moments.[50] Several structural restrictions imposed by the model on the joint distributions of firm wages, employment, wage gains, and labor flows are satisfied in the data, building confidence in our estimated frictions.

[49]In Figure A9 we show the non-parametric relationships for the moments in rows 12, 13, and 14 of Table 3. In Figure A10, we show that adding individual fixed effects in wage growth brings the empirical estimates for the standard deviations of wage growth very close to the model's ones.

[50]Given the arbitrary distinction between targeted and not targeted moments, we decided to simply include as targets all the key relevant moments. The model performance is thus evaluated by its ability to simultaneously match several features of the data despite its relatively limited flexibility.

5.5 Parameter Estimates

We present the estimated spatial frictions in Table 4, and show the remaining parameters in Appendix H.2. Row (1) reports the one-time moving costs, $\hat{\kappa}_{jx}$, as a fraction of the present discounted value of income. Since these costs vary with distance, we present a range of costs for moves between the closest two locations and moves between the farthest two locations. Our estimates indicate moving costs in the range of $3-5\%$ of the PDV of income, implying that an individual earning a yearly salary of 36,000€ for a work life of 45 years faces a moving cost of between 17,453 € and 29,704 €.[51]

Rows (2) and (3) show that a worker employed not in her home location but still in her home region would need to be paid, in real terms, about 7.4% more than in her home location to obtain the same flow utility. Moving away from both home location and region requires a yearly compensation almost 10% higher than at home.[52]

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

Rows (4) and (5) report the estimated search efficiencies, relative to the within-home location level, which is normalized to 100%. Individuals that are in a location away from home and search within that location are slightly less effective than at home, filing only about 90% as many applications per unit of search effort as at home (row 4). More importantly, however, all individuals have a much lower search efficiency for cross-location searches, consistent with evidence that workers search for jobs primarily locally.[53] As before, we provide a range for searches between the two closest locations and between the two farthest locations. Row (5.i) shows that one unit of search effort expended across locations in the non-home region translates into filing only about 1/20th as many applications as in the home location. Cross-location searches directed towards the home region, but not to the home location, are only slightly more effective (5.ii). Row (5.iii) shows that one unit of search effort by workers currently away from their home location that is directed towards the home location generates 24.11% to 17.22% as many applications as searches within the home location. Hence, workers searching across

[51] We discount at the model interest rate of 0.5% per month.

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

[53] See Manning and Petrongolo (2017), Le Barbanchon, Rathelot, and Roulet (2020), Datta (2022).

Table 4: Estimated Spatial Frictions

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

Notes: The table shows the estimated values of the spatial frictions. All parameters used to compute them, according to the formula included in each row, are in Table A27. 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.

locations are about four times as efficient in searching in their home location than in their non-home region. The lower efficiency away from home could reflect social connections, which facilitate finding jobs at home (Burchardi and Hassan (2013), Bailey, Farrell, Kuchler, and Stroebel (2020)).

While we leave the discussion of the remaining parameters to Appendix H, we note here that our model infers an amenity value in the East that is 11% higher than in the West. This additional amenity is consistent with the large fiscal transfers towards East Germany (Henkel, Seidel, and Suedekum (2021)) and it could additionally reflect remaining cost of living differences that are not picked up by our price indices.

6 Labor Misallocation across Firms and Regions

We use the estimated model to study the role of spatial frictions in the allocation of labor across firms and regions. First, we analyze the aggregate effects of spatial frictions and the mechanisms through which they unfold. Then, we turn to the distributional effects across regions and workers' types, and we explore whether the results are robust to changing the number of locations or their relative size. Finally, we study the extent to which the aggregate results are affected by the estimated frictions in the local labor markets. Throughout this section, we present the results by region rather than for individual locations to facilitate the exposition and since the heterogeneity across locations within regions is minimal.

6.1 Aggregate Effects of Spatial Frictions

We recompute the equilibrium keeping all the parameters at their estimated values, but remove all spatial frictions: the moving cost ($\kappa_0 = 0$), the preferences for the home location or region ($\tau_l = \tau_r = 0$), and the differences in search efficiency for searches across and within locations ($z_{l,1} = z_{l,2} = z_r = z_1 = 0$ and $z_0 = 1$). We then compute five core statistics for the long-run steady state equilibrium in the baseline and the counterfactual: (i.) output per capita (and hence labor productivity, p); (ii.) the average of workers' value functions across all employed and unemployed workers; (iii.) average wage, $w_j(p)\,\theta_j^i$; (iv.) average real wage, $w_j(p)\,\theta_j^i/P_j$; and (v.) the share of the overall employment in West Germany.

The results for Germany overall are shown in the first column of Panel (a) of Table 5. Removing all spatial frictions leads to an increase in output per capita, hence in labor productivity, of slightly less than 5%.[54] Despite these relatively modest output gains, the increase in the average worker's value is much larger.[55] The reason is twofold. First, without spatial frictions workers no longer incur the moving cost $\hat{\kappa}_{jx}$ or the utility cost (τ_l, τ_r) when they cross locations. Moreover, workers' search efficiency across locations rises, which increases their continuation value and allows workers to focus on matches with a high taste shock ε. Second, eliminating spatial frictions exposes firms to stronger competition for workers from firms in other locations, which raises wages more than the increase in labor productivity due to a reduction in firms' monopsony rents. We show below that the reduction in monopsony power is responsible for the majority of the aggregate output gains and a sizable share of the increase in workers' value.

Row 5 illustrates that there is net reallocation of labor towards the East, hence, towards the region with, on average, lower productivity. This result could seem counterintuitive: in a neoclassical framework we would have expected labor to reallocate towards the West. However, it is a direct implication of an inherent asymmetry in our frictional setting. In the data, and in our baseline estimation, there are only about a third as many East Germans as West Germans. Therefore, more workers have a strong attachment to the West than to the East due to home bias and search frictions. Once we remove spatial frictions, even though a relatively smaller share of West Germans than East Germans migrate, there is a relatively larger positive labor supply shock in the East, as it is opening up to a larger labor market.

We now further investigate the mechanisms behind our findings. First, we analyze the impor-

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

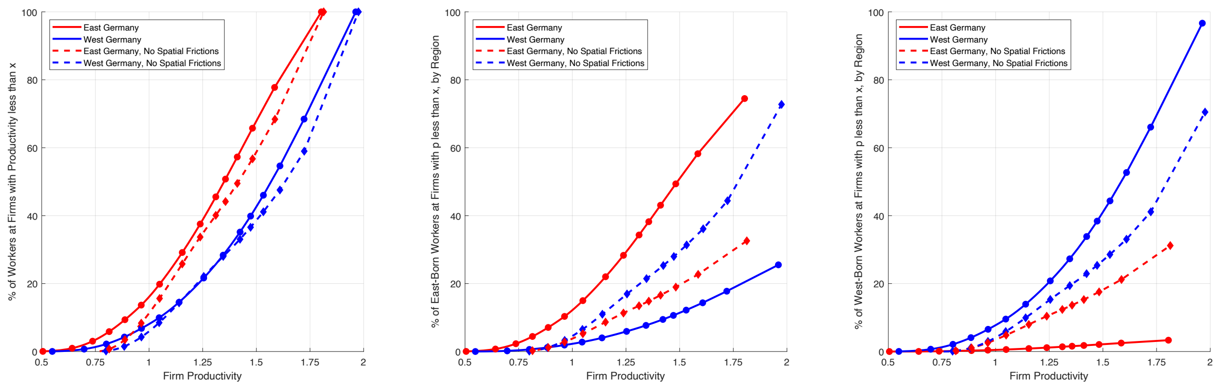
[55] We use the term workers' value rather than welfare since we are, in the counterfactual, effectively changing preferences through the taste spatial friction τ_j^i.

Table 5: 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)	% Workers in West	- 10.9 %	/	- 8.7 %	- 8.2 %	- 0.6 %
			Panel (b): By region				
West	(6)	Output pc	+ 4.2 %	+ 6.0 %	+ 0.4 %	+ 2.5 %	+ 0.1 %
	(7)	Value Function	+ 33.3 %	+ 35.0 %	+ 18.8 %	+ 22.1 %	+ 1.8 %
	(8)	Wage	+ 8.6 %	+ 10.5 %	- 1.5 %	+ 4.1 %	+ 0.8 %
	(9)	Real Wage	+ 9.2 %	+ 11.1 %	- 0.9 %	+ 4.6 %	+ 0.9 %
	(10)	Wage per eff. unit	+ 10.2 %	+ 10.5 %	+ 0.4 %	+ 5.6 %	+ 1.4 %
East	(11)	Output pc	+ 17.0 %	+ 9.6 %	+ 10.0 %	+ 12 %	+ 4.5 %
	(12)	Value Function	+ 53.7 %	+ 46.2 %	+ 36.6 %	+ 39.1 %	+ 8.1 %
	(13)	Wage	+ 24.6 %	+ 16.6 %	+ 6.2 %	+ 13.3 %	+ 7.6 %
	(14)	Real Wage	+ 21.1 %	+ 13.3 %	+ 3.8 %	+ 10.8 %	+ 7.2 %
	(15)	Wage per eff. unit	+ 17.4 %	+ 16.6 %	+ 0.4 %	+ 7.1 %	+ 5 %
			Panel (c): By worker type				
Born West	(16)	Output pc	+ 1.9 %	+ 6.0 %	- 2.1 %	+ 0.3 %	- 0.4 %
	(17)	Value Function	+ 34.3 %	+ 34.5 %	+ 19.8 %	+ 23.2 %	+ 1.9 %
	(18)	Wage	+ 6.0 %	+ 10.6 %	- 5.0 %	+ 1.3 %	+ 0.3 %
	(19)	Real Wage	+ 7.5 %	+ 11.1 %	- 3.6 %	+ 2.6 %	+ 0.8 %
	(20)	% Workers in West	- 27.3 %	/	- 25.1 %	- 23.2 %	- 6.8 %
Born East	(21)	Output pc	+ 15.9 %	+ 8.7 %	+ 11.3	+ 12.1 %	+ 5.1 %
	(22)	Value Function	+ 47.2 %	+ 47.0 %	+ 30.5	+ 32.1 %	+ 6.6 %
	(23)	Wage	+ 23.1 %	+ 14.8 %	+ 10.4	+ 15 %	+ 8 %
	(24)	Real Wage	+ 18.9 %	+ 12.7 %	+ 6.7	+ 11.2 %	+ 6.2 %
	(25)	% Workers in West	+ 43.5 %	/	+ 45.6	+ 41.4 %	+ 20.6 %

Figure 7: Labor Allocation Across Firms and Regions

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



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

tance of within-location reallocation of labor compared to worker reallocation across locations. Second, we discuss the role of the equilibrium response of firms. Finally, we separately analyze the different types of frictions.

The Importance of the Within-Location Allocation of Labor. To analyze the importance of a better allocation of workers to firms within locations, in the second column of Table 5 we recompute the aggregate gains holding fixed the share of workers in each location at the baseline level, thus shutting down migration. We continue to change the within-location distribution of workers and firms' policy functions as in the full counterfactual. We find that shutting down the migration across locations actually *raises* output and wages. This outcome arises because, as already noted, workers migrate towards the lower productivity East in the full counterfactual, decreasing aggregate output and wages.

Panel (a) of Figure 7a analyzes how the within-region reallocation of workers generates the aggregate gains. The figure shows the CDFs of employment to firms of different productivity within East and West Germany for the baseline (solid) and the counterfactual without spatial frictions (dashed).[56]

Removing spatial frictions shifts both distributions to the right as labor reallocates towards the more productive firms. In the baseline economy, spatial frictions partially shield low productivity firms from competition through two margins: i. by reducing the value of unemployment, thus allowing firms to hire workers at a relatively low wage; ii. by limiting the rate at which

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

workers are poached, as they are only rarely poached from firms in the other region. As spatial frictions are removed, these protections are eliminated. Therefore, it becomes harder for unproductive firms to hire and to retain workers, forcing them to shrink. While removing spatial frictions also makes it easier for unproductive firms to hire from the other region, on net the negative effect dominates. As a result, the lowest productivity firms stop posting vacancies as they are not able to offer a higher value than unemployment. This effect is stronger in the East because it has the lowest productivity firms overall. The reallocation towards higher productivity firms is similar in spirit to the within-industry reallocation observed in international trade models such as Melitz (2003) after an economy opens up to trade. Yet, it comes from a very different mechanism: competition for workers in the labor market, rather than for customers in the output market.

We can further unpack the drivers behind the within-region reallocation of labor by decomposing the total labor employed at a firm of productivity p in region j as

$$e_j(p) = \underbrace{\vartheta_j^{-\chi}}_{\text{Tightness}} \underbrace{v_j(p)}_{\text{Vacancies}} \sum_{i \in \mathbb{I}} \left(\frac{\bar{a}_j^i}{\bar{a}_j} \underbrace{\mathcal{P}_j^i(w)}_{\text{Accept Probability}} \underbrace{\left(q_j^i(w)\right)^{-1}}_{\text{Separation Rate}} \right).$$

The first term captures the local market tightness and thus only affects the allocation of labor between, but not within, regions. The other three terms could, in principle, explain the reallocation of labor towards more productive firms. Removing spatial frictions might allow high productivity firms to post relatively more vacancies (high $v_j(p)$), make it easier for them to attract workers upon meeting them (high $\mathcal{P}_j^i(w)$), or facilitate worker retention (low $q_j^i(w)$).

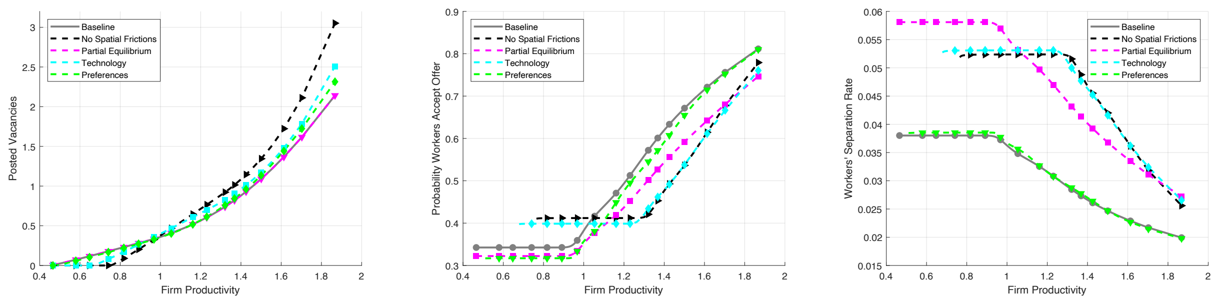
In Figure 8, we plot these three objects as a function of firm productivity, for both the baseline economy (solid gray line) and the economy without spatial frictions (black dashed).[57] Panel (a) shows that the number of posted vacancies contributes positively to the reallocation of labor from low- to high-productivity firms. Going from the baseline to the counterfactual, more productive firms increase their number of vacancies while unproductive firms shrink. The separation rate also contributes positively to the improved allocation of labor (panel (c)): in the counterfactual equilibrium all workers search more intensively, leading to a higher separation rate than in the baseline, but this effect is particularly large at lower productivity firms. The acceptance probability, instead, mitigates the reallocation gains (panel (b)). Workers are relatively more likely to accept offers at lower productivity firms in the economy without spatial frictions. This result is driven by the fact that access to the country-wide pool of unemployed workers, as previously noted, has a larger relative impact on the lower productivity firms.[58]

[57] The plots are for East Germany. The ones for West Germany are similar and are included in Appendix J.

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

Figure 8: Margins of Employment in East Germany

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



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

Large Equilibrium Effects due to Lower Monopsony Power. How important is the change in labor market competition, and the resulting decline in most firms' local monopsony power, for the aggregate gains? In the counterfactual equilibrium, both workers and firms change their behavior. Workers search more intensively across locations and are more willing to accept job offers that are further away. Firms adjust their wages and vacancies to more competition. To disentangle these two effects, we recompute the steady state holding fixed firms' wages and posted vacancies at their baseline values while allowing workers to adjust their search and acceptance behavior.

The results in column 3 of Table 5 show that when firms' wage and vacancy policies are held fixed, the output per capita increases by only 0.5% (row 1). Thus, firms' equilibrium response to more competition is the main driver of the aggregate gains. Intuitively, when firms are not able to adjust vacancies, one of the key drivers of the improved within-allocation is muted, as illustrated by the dashed pink line on top of the gray line in Panel (a) of Figure 8.[59] While the separation rate still rises more for low-productivity firms than for high-productivity ones (Panel (c)), contributing to a better allocation of workers, this channel alone has only a modest effect.

Lack of Opportunities or Unwillingness to Take Them? There are significant complementarities between the different types of spatial frictions. Our model contains both *technological* spatial frictions imposed by the moving cost κ and the search productivity z, and *preference* spatial frictions due to home preferences τ. Technological frictions could be affected by policy. For example, a faster railway system or rental subsidies to facilitate the housing search could decrease κ, while an integrated online job portal could reduce z. Instead, preference frictions are plausibly harder to affect, as they are typically a slow moving object that changes across generations (Alesina and Fuchs-Schündeln (2007)).

[59]In Appendix J we replicate Figure 7 for this alternative counterfactual.

To analyze their effects separately, we recompute the equilibrium of the economy when we remove either only the technological spatial frictions or the home bias. We find substantial aggregate gains from removing technological barriers that are about a third to one half as large as the baseline (column 4 of Table 5). In contrast, removing home preferences generates only small gains (column 5 of Table 5). The blue and the green line in Figure 8 illustrate the drivers behind these effects.[60] When only home preferences are eliminated, workers' separation decisions remain nearly unchanged and vacancies shift by less than when the technological spatial frictions are removed, leading to smaller gains. However, there are important complementarities: summing over the aggregate gains from both exercises in Table 5 yields only about half the effect of removing both sources of frictions at the same time.

Our results show that both a lack of opportunities and an unwillingness to take them contribute to the aggregate effects in Germany. The technological spatial frictions mainly generate a lack of opportunities: even in the absence of home preferences, East-born individuals have a hard time accessing jobs in the West because they do not obtain job offers, and many of the ones they find are not good enough to compensate for the cost of moving there. Instead, the home preferences affect individuals' willingness to take the available opportunities: many East Germans remain in the East because, everything else equal, they are more likely to accept offers received from their birth-region. To generate large effects from integrating the labor market, both sources of spatial frictions must be addressed simultaneously.

6.2 Distributional Effects of Spatial Frictions

We next show that spatial frictions also have large effects on the distribution of resources across regions and worker types.

Differences by Region. We first examine the effects of removing spatial frictions separately for individuals in the West and in the East of Germany, for all five exercises run before (Panel (b) of Table 5).[61] We also report the wage per efficiency unit, $w_j(p)$, to highlight the difference with the average wage $w_j(p)\,\theta_j^i$, which depends on the composition of workers (θ_j^i) in each region.

Column 1 highlights that the baseline gains from removing spatial frictions are much larger in the East than in the West. There are two main reasons for this result. The first one is mechanical: despite similar observable characteristics, we estimated a large gap between East and West workers in unobservable skills from the AKM (see row 1 of Table 2). Therefore, as West workers move East and East workers move West, average human capital improves in

[60] In Appendix J we replicate Figure 7 for these alternative counterfactuals.

[61] In the model, individuals move continuously across locations. Nonetheless, we can compute the outcomes for the individuals that are, in our long-run steady state, in either East or West Germany. The computed statistics will, of course, take into consideration the possibility that individuals move across locations and regions.

the East and declines in the West, which can be seen by comparing the changes in wages and wages per efficiency unit in the two regions. Second, the reallocation of labor away from lower productivity firms is stronger in the East since there are more low productivity firms in that region.

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

Column 2 highlights that worker migration across regions is important for the distributional effects. When worker mobility across regions is shut down, the output and wage gains in East Germany fall by nearly half. A large part of the East German gains is due to the increase in average human capital resulting from the inflow of West German workers. Instead, in West Germany, migration has a negative effect on output and wages. The take-aways from the counterfactual exercises in columns 3-5 are qualitatively similar to before.

Differences by Worker Type. Panel (c) shows the effect of removing spatial frictions for East versus West Germans. While everyone benefits, East Germans see a larger increase in their output per capita, wages, and values than West Germans since a sizable share of them move from the East to the high productivity West. Panel (b) of Figure 7 illustrates this move by plotting the semi-CDF of East Germans in each region.[62] The share of East Germans in the West rises significantly.

For West Germans, as shown in Panel (c) Figure 7, the net migration towards the East leads them, on average, to work for lower productivity firms than in the West. Nonetheless, their wage rises because of the equilibrium increase in average wage in both regions, and from the overall improvement in the allocation of labor.

Implications for the West-East Gaps. Table 6 provides another perspective on the results by showing the percentage differences in our variables of interest between East and West Germany and between East and West German workers. For reference, Column (1) presents the East-West gaps in the baseline economy. Column (2) shows that eliminating spatial frictions shrinks the gaps in output, value, and wages considerably, but does not eliminate them. The remaining gaps are due to the average higher productivity of firms in the West, the higher

[62] The semi-CDF means that each line does not end at one but at the share of East German workers in each region. Adding up the last point on the two solid lines or on the two dashed lines gives one.

Table 6: West-East Gaps with Reduced Spatial Frictions

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

estimated amenity in the East and the presence of labor market frictions. The higher amenity in the East allows firms there to still retain workers while paying a lower real wage.[63]

The gap between East and West Germans is purely due to the estimated differences in workers' skills θ. Even in the absence of spatial frictions, West Germans earn a higher wage, produce more GDP per capita, and have higher value due to their higher estimated skills.[64]

6.3 Increasing the Number of Locations and Market Size Effects

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

First, we vary the number of locations. In principle, the large role we find for the within-location reallocation of labor could be due to the fact that geographic units in our model are large, thus limiting the possibility of between-location reallocation. To assess this concern, we solve a version of our model in which we allow for more locations, splitting each of the four

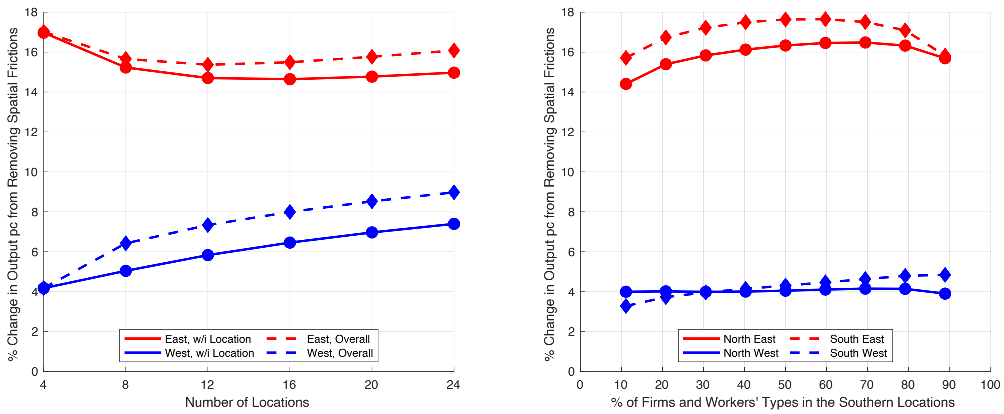
[63]Since the residual real wage gap is 13.6% and we estimated an amenity difference between East and West of 11%, there is, even once we account for amenity differences, a roughly 2.6% higher real wage in the West.

[64]A small difference remains between East and West Germans even in wage per efficiency unit since West Germans, due to their higher skills, search more intensively for jobs.

Figure 9: Aggregate Cost of Spatial Frictions as a Function of Size and Number of Locations

(a) Number of Locations

(b) Location Size



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

locations in the benchmark model into either 2, 3, 4, 5, or 6 sub-locations. We randomly draw each sub-location k's average firm productivity, $A_j(k)$, from a normal distribution with mean equal to the overall location's estimated productivity, A_j, and standard deviation equal to the East-West productivity gap to allow for possibly large gains from the reallocation of labor across the sub-locations. We keep the spatial frictions exactly as estimated in the baseline, and we split the workers' types to match the new locations.[65]

Figure 9a presents the output per capita gains from removing spatial frictions as a function of the total number of locations in the economy. The solid lines show the gains due to the reallocation of labor *within* the locations, averaged across all locations in East and in West Germany, respectively. The dashed lines provide the total gains, i.e., including those from worker reallocation across locations. Overall, we continue to find large gains from the within-location reallocation of labor even as we increase the number of locations. While reallocation across locations becomes more important as the number of locations grows, most gains are within-location in all cases. Intuitively, there is significant scope for within-location reallocation due to substantial heterogeneity across firms, and congestion forces due to prices and labor market tightness limit the gains from labor reallocation across space.

Second, we vary the labor market size. In principle, the larger effects of removing spatial frictions for East Germany could be driven not by the lower productivity of East firms, but by

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

the smaller size of the East German labor market in terms of the number of firms and workers. As a result, spatial frictions could be more binding in the East. To assess whether the size of a location affects its aggregate gains, we proportionally vary the mass of firms (M_j) and workers $\left(\bar{D}_j^i\right)$ that are in the South versus in the North in both East and West Germany, keeping the total mass of workers and firms in the overall region and the other structural parameters constant. Figure 9b shows that increasing the mass of workers and firms in the South relative to the North has only small effects on the aggregate gains in both locations. This result is driven by the interplay of two counteracting forces. On the one hand, without spatial frictions firms in smaller locations have a bigger relative increase in the mass of workers that can now apply to their vacancies. On the other hand, they face a relative bigger increase in the competition for labor from firms in other locations. These two effects roughly balance each other out so that on net the market size is not an important driver of the regional heterogeneity.[66]

6.4 The Role of the Local Labor Market for Aggregate Gains

Since the aggregate impact of spatial frictions is mediated by their impact on the allocation of labor across firms, our results naturally depend on the micro-level details of the labor market, as we next show.

We vary, one at a time, three core parameters which modulate the strength of the labor market frictions: i. the vacancy cost (ξ_0), which affects the overall mass of vacancies posted by firms; ii. the variance of the preference taste shocks (σ), which affects the allocative power of wages; iii. the elasticity of workers' search cost (ε), which modulates the ability of workers to move up the job ladder by searching for better jobs while at the low rungs. We show that varying these parameters has a significant impact on within-location labor market moments and on the aggregate gains, but does not affect the East-West wage gap.

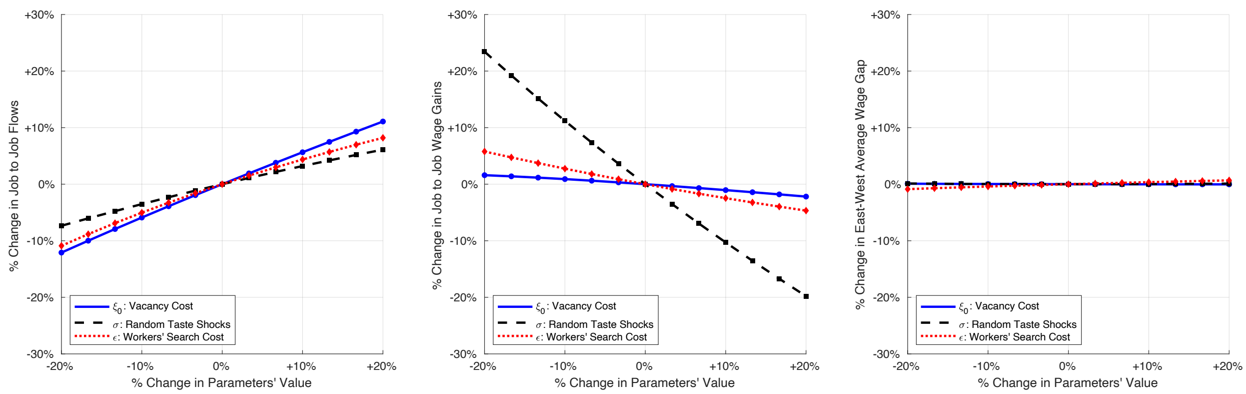
We first show the effect of these parameters on within-location labor market moments and on the wage gap in Figure 10. Panel (a) illustrates that within-location job-to-job flows increase relative to the baseline with each parameter. Panel (b) shows that the within-location wage gains for movers decline sharply with the variance of preference shocks σ, but are relatively unaffected by the other two parameters.[67] When σ is large, workers' moves are more frequently due to preferences rather than wage differences, reducing the average wage gain. Finally, Panel (c) highlights that changing the labor market frictions has no significant effect on the aggregate wage gap between East and West Germany since, as argued in Section 5.1, these parameters mainly affect the distribution of labor within, rather than between, regions.

[66] This result is possibly not very surprising as there are no real scale economies in our model. The matching function has constant returns to scale in vacancies and applications, and each location and each firm produce an identical good.

[67] While we report in the figure only the within-location moments, we note that the changes in cross-location flows and wage gains are very similar (in percentage terms).

Figure 10: Sensitivity of Micro and Macro Moments to Labor Market Parameters

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



Notes: We vary three different parameters modulating the labor market frictions, recompute selected targeted moments, and compare them with the baseline economy. The left panel shows the job to job flows (the lines marked with a cross are the job flows within region). The middle panel shows the wage gains obtained from move within region (marked with a cross) and between regions. The right panel shows the gap in average wage between West and East Germany.

We next compute, just as in Section 6.1, the gains from removing spatial frictions in these alternative economies with different labor market frictions. As Panel (a) of Figure 11 shows, the aggregate gains in output per capita decline substantially for higher values of the labor market parameters, i.e., as labor mobility increases. For example, in an economy with 10% higher vacancy costs, the aggregate gains are reduced by a quarter compared to the baseline, from 4.7% to 3.9%. This result is intuitive: higher labor mobility implies smaller potential gains from improving the within-region allocation of labor. This result is also important: two economies could look identical in terms of their wage gap between regions (as shown in Figure 10), yet removing spatial frictions could lead to very different aggregate outcomes dependent on the economies' labor market frictions.

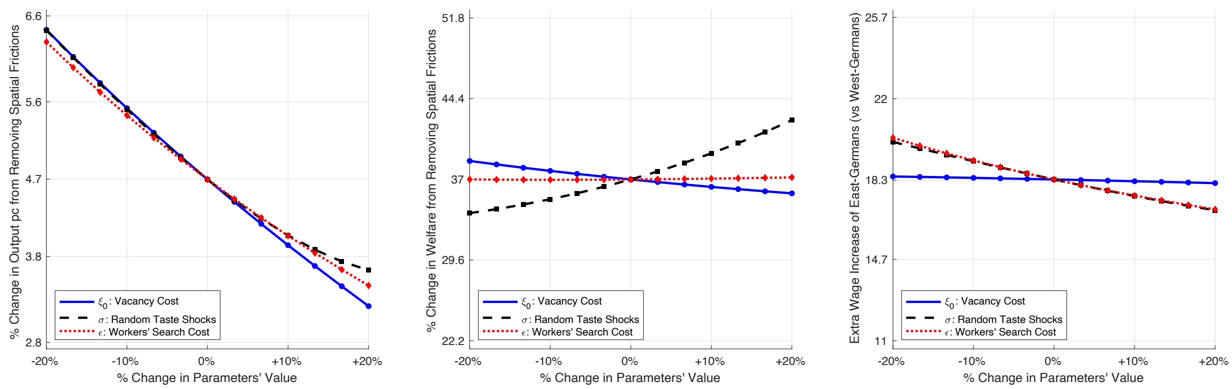
The impact of the spatial frictions on either the workers' value or the relative wage of East Germans is much less sensitive to the value of the labor market parameters (Panels (b) and (c)). For these two statistics, the allocation of labor within location is less relevant: removing spatial frictions 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.

7 Conclusion

This paper's main finding is that taking into account how local labor markets function, and how they are hampered by search and matching frictions, is important to quantify the effects of

Figure 11: Sensitivity of the Aggregate Effects to Labor Market Parameters

(a) Output per Capita 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 three panels show the effect on GDP per capita (left), workers' value function (middle) and relative wage increase of East-born (right), plotted as a function of the change in the primitive parameters relative to the baseline. To ease comparability across the different panels, we standardized the y-axis to cover changes of + 40 % to - 40 % relative to the baseline value of the statistic.

spatial frictions on the aggregate economy. Barriers impeding labor mobility across space affect firms' local monopsony power, which, in turn, shapes the allocation of labor to firms and thus aggregate productivity.

To reach this overall conclusion, we design a model which encompasses both spatial and labor market frictions, allowing us to study the joint allocation of labor across firms and locations. Bringing the model to data from Germany, we learn four new insights that make our core takeaway concrete and that are relevant beyond the context of Germany.

First, removing spatial frictions can improve the allocation of workers to firms within locations, generating aggregate gains in addition to the typically emphasized reallocation of workers across locations. Second, spatial frictions provide firms with local monopsony power and allow unproductive firms to grow. When spatial frictions are removed, the additional competition for workers leads to the reallocation of jobs towards the most productive firms, possibly generating large aggregate gains, as we find in our context. Third, the aggregate gains from removing spatial frictions can vary substantially across economies dependent on their local labor market frictions, even when these economies have the same wage gap between locations. Analyzing spatial wage gaps without firm-level data may therefore give an incomplete picture. Finally, even in a context, such as ours, in which the within-location reallocation of workers is important for the aggregate gains, reallocation across regions is still important for the distributional effects, as workers born in a low productivity locations are trapped there by spatial frictions.

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