Labor Misallocation Across Firms and Regions*

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Abstract

We develop a frictional labor market model with multiple regions and heterogeneous firms to study the joint allocation of labor across firms and regions. We estimate the model with matched employer-employee data from Germany. We find that, despite the large West to East wage gap, the main cost of frictions to labor mobility across space is, perhaps suprisingly, to misallocate labor across firms *within regions*, rather than across them. The reason is that spatial frictions raise firms' local monopsonly power by shielding them from competition, allowing low productivity firms to expand in both East and West Germany. Overall, we show that the aggregate impact of spatial frictions can vary substantially across economies dependent on their local labor market frictions.

JEL: J6, O1, R1

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1 Introduction

Within many countries, large regional differences in real wages and labor productivity have persisted for decades.[1] A substantial literature has shown that spatial frictions, such as moving costs or home bias, might play an important role behind this lack of regional convergence. By preventing workers from leaving unproductive regions, these frictions could entail large aggregate losses due to worker misallocation across space (Bryan and Morten (2019)).

In this paper, we propose and quantify a new margin through which spatial frictions 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 barriers to labor mobility across space have an additional – yet under-studied – 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 provide local monopsony power. By shielding low productivity firms from competition from other regions, spatial frictions allow these firms to stay in business and to attract workers. We estimate that the aggregate losses due to this mechanism in Germany amount to about 5% of GDP. Our findings highlight that the aggregate losses due to spatial barriers depend on the local labor market frictions: 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 them as a function of the labor market frictions.

Our paper consists of three parts. In the first part of the paper, we use micro data from the German Federal Employment Agency to document three sets of facts, which motive our focus on the joint allocation of labor across firms and regions and justify the ingredients in 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 show a large wage gap between East and West Germany, but also that there is a wide overlap between the wage distributions in the two regions, and that, conditional on the same wage, firms in the East are considerably larger. As a result, it would be possible to completely close the regional gap even just by reallocating labor within East 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 increase when moving West, suggesting very large gains from regional integration. At the same time, we also show that workers experience sizable wage gains for any job to job move, even within region,

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

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

Finally, we use again the LIAB data to study workers' flows. We show that workers' job ladder is distorted. Workers switch jobs mostly locally and exhibit home bias (i.e., workers have a preference for their home location), leading to a job ladder that is characterized by frequent return migration of workers that have left their home. Hence, any gain from cross-regional migration may be washed out if workers eventually return home to low productivity firms.

Motivated by the empirical facts, we develop a general equilibrium framework of a frictional labor market to study the allocation of labor across firms and regions. Our model is a multi-region job posting model à la Burdett-Mortensen (e.g., Burdett and Mortensen (1998)) with heterogeneous firms, 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. Workers and firms meet according to a matching function that is concave in applications and vacancies, as in Diamond-Mortensen-Pissarides models (e.g., Pissarides (2000)), generating random job offers within each region and an endogenous labor market tightness. Search is thus directed across regions, but random within region, which is important for identification of the spatial frictions. Despite the framework's richness, we derive a tractable solution represented by a system of differential equations.

Our model provides a framework 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. For example, tax vouchers may increase mobility if spatial frictions represent moving costs, but less so if they are due to worker preferences for their home region, which are very difficult to affect with policy.

While all model parameters and frictions are jointly identified, we provide a heuristic identification argument. 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 discipline the unobservable endogenous distribution of job offers in each region. Given a set of within-region 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 search efficiency across space. Relatively lower worker flows across regions, compared to between firms within region, indicate that workers are less successful in applying for jobs in other regions.

We estimate the model with four sub-regions of Germany – which we refer to as *locations* – corresponding to the Northwest, Southwest, Northeast, and Southeast, and incorporate four worker types reflecting the four possible home locations. The model matches the data well, despite being relatively parsimonious with 21 parameters being used to match 305 micro and aggregate moments.

The model estimates imply non-negligible spatial barriers, especially due to the limited ability of workers to access job opportunities that are further away. 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 unpack the different types of spatial frictions and to distinguish them from general labor market frictions.

We compute a series of counterfactual equilibria to quantify the aggregate and distributional costs of spatial frictions. Removing all spatial frictions, we find that GDP per capita in Germany would increase by almost 5%, and average real wages would rise by 9%. Our main finding is that these sizable aggregate gains are purely 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 monosony power by exposing them to more competition for workers from other locations, which forces unproductive firms to shrink or to exit the market and leads to a reallocation of labor towards high productivity firms. Workers obtain sizable wage increases as a result of the fiercer competition for labor.

The gains are not equally distributed across locations and workers' types. When spatial frictions are removed, East Germany sees a much larger increase in GDP per capita of 17% and East Germans see their wage rise by almost 25%. For these distributional effects, both the allocation of labor within locations and across locations is important. First, since average productivity in East Germany is lower, there are more unproductive firms there which are particularly negatively affected by the increased competition for labor as we remove spatial frictions. Second, we estimate that West Germans have higher unobserved skills. Since eliminating spatial frictions reduces the sorting of workers across space, the average skill-level of the labor force in East Germany rises, leading to higher productivity gains in the East. Finally, removing spatial frictions gives East Germans better access to the higher wage jobs in the West and reallocates them towards that region. Overall, the wage and productivity gaps between East and West Germany are considerably reduced, yet not totally eliminated.[2]

We decompose the aggregate gains into the firms' equilibrium response and into differences in the workers' job ladder driven by changes in workers' acceptance probabilities and search effort. Our estimated model highlights that the aggregate gains are mainly driven by the endogenous response of firms to more competition, rather than by the ability of workers to obtain more viable job opportunities from the entire country. When we hold fixed firms' wage posting and vacancies, removing spatial frictions generates only a modest increase of 0.5% in GDP per capita, and even a small reduction in average wage. Yet, even shutting down the equilibrium response of firms there are large distributional consequences since these are mainly driven by the allocation of labor across rather than within regions. In this economy, East born individuals still benefit substantially, showing the importance of equality of opportunities, but West born workers are negatively affected as they are displaced towards the less productive East.

We find strong complementarities between the spatial frictions generated by technological parameters (the moving cost and the spatial search frictions) and by the frictions generated by preferencess (the home bias). Removing each of these two types of frictions separately generates, on average, overall only about one quarter of the gains of removing both sources of frictions at the same time. Thus, to truly reap the gains from an integrated labor market, workers need to have access to opportunities to move to more productive locations (technology), but also be willing to accept these opportunities (preferences).

Finally, we demonstrate that the gains from removing spatial frictions decline sharply when the labor market frictions within each location fall. The reason is intuitive: with more labor mobility within each location, labor is already relatively concentrated at the most productive firms, hence the marginal gains from removing spatial frictions are limited. We also show that the overall average wage gap between two locations does not depend in general on the degrees of labor market frictions. Consequently, we conclude that two economies could look identical in terms of their wage or productivity gap between regions, yet removing spatial frictions could lead to very different aggregate gains.

Overall, our results highlight the importance of studying the allocation of labor within and across regions in a unified general equilibrium framework, hence to study *space* and *firms* jointly.

Literature. Our paper contributes to several strands of literature.

First, we contribute to the literature quantifying the size of spatial barriers and their aggregate effects (Caliendo, Opromolla, Parro, and Sforza (2017) and Bryan and Morten (2019)).[3] This literature has used observed worker flows and average wage differentials across space to

[2] They are not totally eliminated because we estimate a higher average productivity of West German firms, which implies that they pay higher wages due to the presence of labor market frictions.

[3] See also Artuç, Chaudhuri, and McLaren (2010), Kennan and Walker (2011), Caliendo, Dvorkin, and Parro (2019).

estimate the size of the moving costs. Since worker flows in response to average wage gaps are relatively modest, even after accounting for compensating disamenities, the papers infer large moving costs, which suggest substantial aggregate gains from reallocating workers. Our framework allows us to benchmark worker mobility across space to mobility across firms in a frictional labor market. We find that, despite sizeable spatial barriers, the aggregate gains from removing them are modest because most of the labor misallocation is within regions, and removing spatial barriers does not substantially improve the within-region allocation of workers to firms. Overall, we argue that firms, and firm level-data, should have a prominent role in the analysis of spatial wage gaps.

Second, a recent literature has used panel data to study the observational returns from migration and to quantify the contribution of workers' sorting to regional wage gaps (see Hicks, Kleemans, Li, and Miguel (2017), Alvarez (2018), and Lagakos, Marshall, Mobarak, Vernot, and Waugh (2020)).[4] We show that the interpretation of panel data used in this literature can be misleading. In our setting, the wages of East-born workers increase steeply when moving West, which the cited literature would interpret as evidence of a large causal effect of working in the West, hence of large returns from reducing spatial barriers. This conclusion does not take into account, however, that labor markets are frictional, and that all job movers are selected − they must have received a good enough job offer to move. Moreover, removing spatial barriers can lead to equilibrium effects. Our work controls for movers' selection by benchmarking the wage gains of movers between regions to those within regions, and computes the aggregate gains in equilibrium. We conclude that removing spatial frictions provides smaller gains than implied by an a-theoretical interpretation of the data.

Third, our work is related to job ladder models à la Burdett and Mortensen (1998) with labor mobility across sectors or space. Schmutz and Sidibé (2018) build a partial equilibrium model where identical workers receive job offers both from their current location and from other locations. Consistent with our work, they estimate relatively small moving costs and sizable search frictions across space. However, due to the partial equilibrium assumption their paper cannot study the aggregate effects of removing these spatial barriers, and due to the assumption of homogeneous labor the paper cannot study the distributional effects of spatial frictions. Bradley, Postel-Vinay, and Turon (2017) analyze wage posting and employment in a Burdett-Mortensen setup in the presence of an exogenous public sector, and Meghir, Narita, and Robin (2015) develop a general equilibrium model with two sectors to study the allocation of labor between the formal and informal sectors in Brazil. In both papers, workers receive identical job offers from both sectors *independently* of their current employment status. As a result, there is one unified labor market, and the wage function is continuous as in the standard Burdett-Mortensen model. In our model, workers' probability of receiving and accepting offers

[4] Other relevant papers on sorting, using different methods, are Young (2013), Lagakos and Waugh (2013).

depends on their identity and their current location due to the presence of spatial frictions, which could make the wage functions discontinuous in principle. We resolve this problem by introducing extreme value shocks, building on earlier insights to obtain tractable solutions for discrete choice problems from the trade literature (e.g., Eaton and Kortum (2002)).[5]

Last, our work is related to the literature on East German convergence (or the lack thereof) after the reunification (e.g., Burda and Hunt (2001), Burda (2006)). This literature has studied the possible drivers behind the East-West wage gap and the nature of migration between the two regions (Krueger and Pischke (1995), Hunt (2001, 2006), Fuchs-Schündeln, Krueger, and Sommer (2010)). Uhlig (2006, 2008) shows that the persistent East-West wage gap is consistent with network externalities, which could discourage firms from moving to the East. In contrast to this work, we take the distribution of firms in each region as exogenously given and do not explicitly model the source of the productivity differences.[6] Instead, we focus on spatial barriers to worker mobility and estimate the aggregate effects of removing them.

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 and Section **??** discusses how to unpack spatial frictions. We estimate the model in Section 5 and we use it to quantify the aggregate and distributional effects of spatial frictions in Section **??**. Section 7 concludes.

2 Data

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

The BHP is a panel containing a 50% random sample of all establishments in Germany with at least one employee liable to social security on June 30th of a given year. The data are based on social security filings and exclude government employees and the self-employed. Each establishment in the BHP is defined as a company's unit operating in a distinct county and industry.[7] 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-

[5]Two other related papers are Hoffmann and Shi (2016) and Bilal (2019). The first studies a two-sector Burdett-Mortensen model with no mobility frictions; the second studies unemployment differences across space.

[6]For recent related work that models the endogenous productivity differences across regions, see Fajgelbaum and Gaubert (2020); Bilal (2019); Schmutz and Sidibé (2021).

[7]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.[8] 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 we will use 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 beginning of an unemployment spell for unemployed workers and then added to all observations of that year. Since the social security reporting regulations do not prescribe which residence to report for workers with multiple residences, some workers can 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.[9] 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

[8]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.

[9]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 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

In this section, we provide descriptive evidence from Germany to motivate our focus, our model, and the relevance of our setting. We document three sets of facts: (i) there is significant heterogeneity in wages both across regions and across firms within regions; (ii) workers climb a job ladder that is distorted by gravity and home bias; (iii) workers obtain large wage gains when moving away from their home region, but also when moving across firms within-region.

3.1 Significant Wage Heterogeneity Between and Within Regions

We first show that there is significant wage dispersion across space. Figure 1a plots the average real wage in each county in the period 2009-2014 from the BHP, and shows that there are sizeable cross-county wage differences. What stands out, however, is the large real wage difference between East and West. To examine whether this wage gap is due to observables, we run firm-level regressions of the form[10]

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

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 a 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.[11]

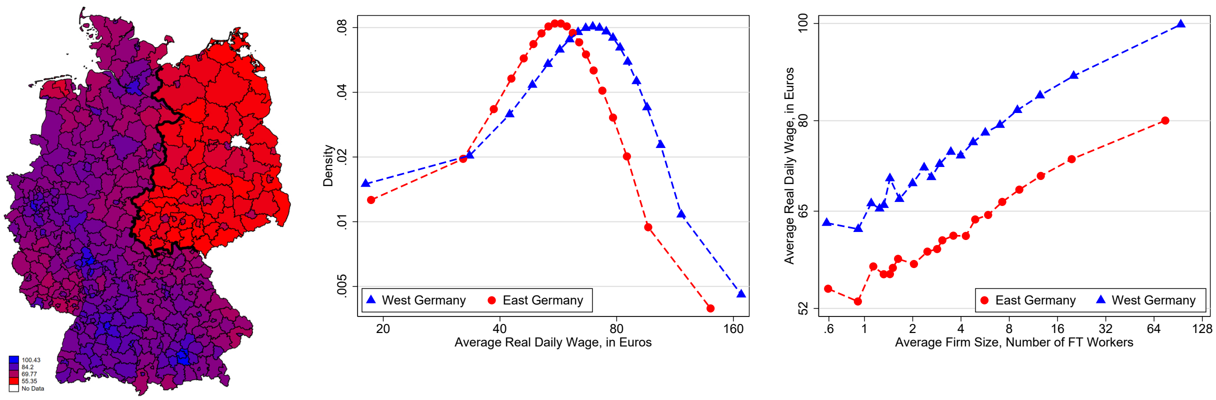
While the wage gap between East and West Germany is striking, there is also significant wage heterogeneity within each region. Figure 1b plots PDFs of firms' average real wage from the BHP, separately for both East and West Germany. We residualize log real wages by regressing them on year dummies and 3-digit industry dummies to remove across industry variation. The figure shows that the average wages by region mask substantial wage dispersion: the wage

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

[11] The detailed regression table is in Appendix X.

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 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. Wages and size are residualized by regressing their log values on 3-digit industry dummies and time dummies, for East and West Germany separately. We generate the cleaned wage and size as the residuals from these regressions plus their means and transform these log variables back into levels.

gap between the lowest- and highest-paying firms in each region exceeds the average wage gap between East and West.[12] Moreover, there is significant overlap between the two distributions.

We analyze the within-region wage dispersion further by plotting the average firm size against the firms' average real wage for twentiles of the firm size distribution in Figure 1c. Wage and size are residualized by year and industry dummies. Average wages increase significantly with firm size in both regions, suggesting the presence of a job ladder. Additionally, conditional on the real wage paid, East German firms are larger than West German ones, suggesting the presence of frictions that shield East German firms from West German competition.

In Supplemental Appendix M[13], we provide some additional robustness checks. We show that the between-region wage gap is persistent over time, similar for all industries and across counties of different education or gender composition, and that there are no clearly delineated regional differences in tax rates.

[12] In Supplemental Appendix M, available on the authors' websites, we show that there is similar wage dispersion across firms even within the same county.

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

3.2 Lower Worker Mobility Across Than Within Regions

Spatial frictions may alter the allocation of workers to firms within regions by affecting the job ladder that workers climb. We next show that workers switch jobs mostly locally and exhibit *home bias* (i.e., workers have a preference for their birth location), leading to a distorted job ladder that is characterized by frequent return migration of workers that have left their home.

We estimate a gravity regression for workers' flows between counties to illustrate the impact of distance, geographical barriers, and home bias on worker mobility. 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.[14]

We define job-to-job switchers as workers that change jobs between two firms without an intermittent unemployment spell. Let $n^h_{o,d,t}$ be the number of workers with home region h that were in a job in county o in year $t-1$ and that have made a job switch 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 both East and West Germany.[15] We use these shares to fit the gravity equation

$$\log s^h_{o,d} = \delta^h_o + \gamma^h_d + \sum_{x\in\mathbb{X}} \phi_x D_{x,o,d} + \rho \mathbb{I}_{R(o)\neq R(d)} + \epsilon^h_{o,d}, \tag{2}$$

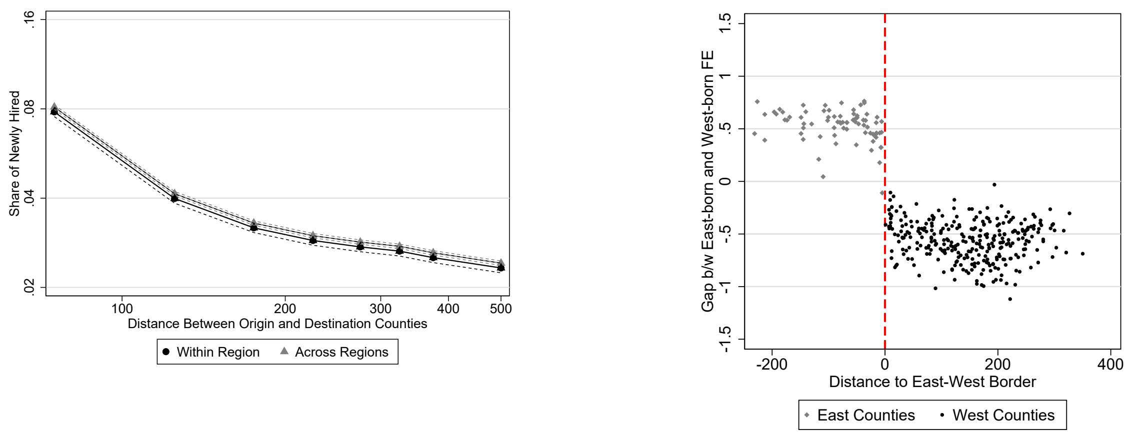
where δ^h_o and γ^h_d are county of origin and destination fixed effects, respectively, which differ by workers' home region, $D_{x,o,d}$ are dummies for buckets of distance traveled between origin and destination, and $\mathbb{I}_{R(o)\neq R(d)}$ is a dummy that is equal to one if the job switch is between East and West Germany. The set of buckets $\mathbb{X}$ contains seven 50km intervals from 50km-99km onward

[14] 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.

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

Figure 2: Results from the Gravity Equation: Geography versus Home Bias

(a) Geography (b) Identity: Destination FE



Source: LIAB. The figures plot results from specification (2). 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 former border. We normalize the fixed effect coefficients for each worker type by their mean and plot counties in the East with a negative distance.

to 350km-399km and an eighth group for counties that are further than 399 km apart. The term $\mathbb{I}_{R(o)\neq R(d)}$ captures any geographical barriers beyond distance affecting mobility between East and West Germany. The home-region specific fixed effects δ_o^h and γ_d^h capture the fact that some counties may be more attractive to workers of home region h, for example due to preferences, comparative advantage, or possibly due to a social network that allows them to find job opportunities.

Figure 2a plots the estimated distance coefficients ϕ_x (black line), which we re-normalize into interpretable shares of switchers.[16] Workers move mostly locally, and job switches become significantly less likely for counties that are further apart. The gray line plots the same results for cross border flows (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 former East-West border.

Figure 2b 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.[17] The figure shows that East individuals have significantly

[16] We show the full list of estimated coefficients of regression (2) in Supplemental Appendix O.

[17] 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)	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 shows the share of these workers that have ever had a full-time job in their non-home region over the entire sample since 1993. Row 2 shows the share of workers that returned to a job in their home region after their first job in the non-home region, and row 3 presents the average number of years away.

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 county. Conversely, East-born workers are less likely to move to counties in the West. Supplemental Appendix O provides additional robustness checks for different sub-groups of the population and for different definitions of cross-border mobility.

While both distance and home bias hamper worker mobility, the labor markets of East and West Germany are, in fact, connected. Rows 1-2 of Table 1 show that on average 1% of all employed West and East Germans switch jobs within-region in an average month, and 0.06% of East Germans switch jobs across regions. Thus, slightly more than one in twenty East German job movers switches jobs across regions. Row 3 illustrates that overall, 4.6% of West-born and 23.9% of East-born have at some point had a full-time job in the other region. 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 2-3).[18] Thus, workers climb a country-wide job ladder, but this ladder is distorted relative to a benchmark without spatial frictions by workers' frequent return migration. This return migration affects firms' wage posting strategy in equilibrium and impacts the within-region allocation of workers to firms. We present additional statistics on movers in Appendix B, and show that the share of workers away from their home region has been relatively stable over the recent period.[19]

3.3 Large Wage Gains of Movers Across Regions

We finally show that workers obtain large wage gains when moving away from their home region, but also when moving jobs within-region. For moves between East and West Germany,

[18]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.

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

we distinguish between migration and commuting. The distinction is useful 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. All other moves between East and West are defined as commuting.[20] We provide several summary statistics on our migration measure in Appendix B.

Let d_{it}^{x} be 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. To visualize an individual's wage dynamics around the time of a job-to-job move, we run a standard system of local projections, consisting of one regression for each time period $\tau \in \{t-3, ..., t-1, t+1, ..., t+5\}$ around t:[21]

$$\Delta \log(w_{i\tau}) = \sum_{s \in \mathbb{S}} \beta_{s,\tau}^{West} d_{it}^{s}(1 - \mathbb{I}_i^{East}) + \sum_{s \in \mathbb{S}} \beta_{s,\tau}^{East} d_{it}^{s} \mathbb{I}_i^{East} + B_\tau X_{it} + \epsilon_{it}, \tag{3}$$

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. 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.[22] The variable $\mathbb{I}_i^{East}$ is a dummy for whether an individual's home region is East Germany. Finally, the controls X_{it} include dummies for the current work region, home region, and their interaction, 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 $\beta_{s,\tau}^{West}$ and $\beta_{s,\tau}^{East}$ 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 3a plots the estimated wage gains for East-to-West migration – i.e. the predicted wage from the relevant coefficients $\beta_{s,\tau}^{West}$ and $\beta_{s,\tau}^{East}$, translated into levels, and normalized around the wage level prior to the year of the migration. The dashed lines in Figure 3b present the wage gains for West-to-East migration. The figures highlight that workers moving out of their home region see their wage increase steeply. East-born movers to the West

[20] 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.

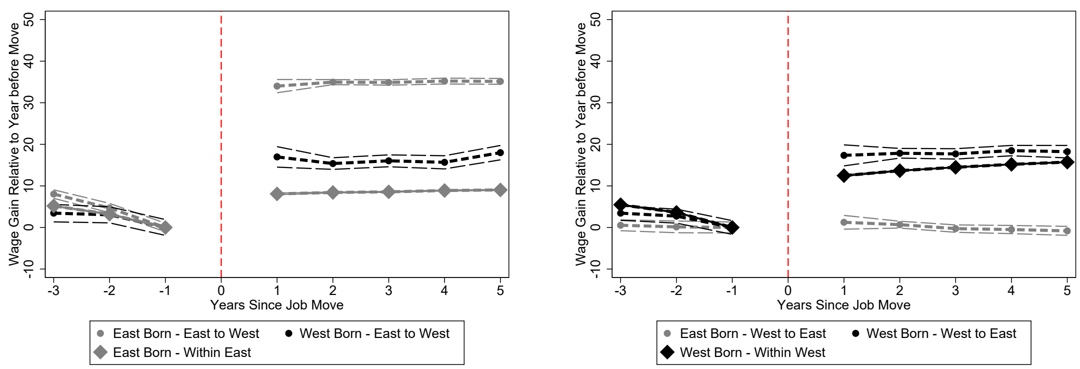
[21] We pool together all the data for time periods t from 2004 to 2014 thus creating an unbalanced panel. In general, working with an unbalanced panel could be problematic. In our application, we are less concerned because: i) we do not observe post-trends; and ii) we are mostly interested in the wage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

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

Figure 3: 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 (3) for $\tau \in \{t-3, ..., t-1, t+1, t+5\}$. We then sum up the coefficients starting at $\tau = -3$ to obtain for each period τ the sum $\sum_{u=-3}^{\tau} \beta^{i}_{s,u}$, where $i \in \{\text{West, East}\}$, and subtract from this sum the term $\sum_{u=-3}^{-1} \beta^{i}_{s,u}$ to normalize the coefficients with respect to period $\tau = -1$. The dotted lines represent the 95% confidence intervals. The dashed lines in the top left panel show the normalized coefficients for $\beta^{West}_{EW,\tau}$ and $\beta^{East}_{EW,\tau}$, and the gray line with diamonds shows $\beta^{East}_{EE,\tau}$. The dashed lines in the top right panel show the normalized coefficients for $\beta^{West}_{WE,\tau}$ and $\beta^{East}_{WE,\tau}$, and the black line with diamonds shows $\beta^{West}_{WW,\tau}$.

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. Moves to the East, instead, are associated with sizable wage gains for West-born workers and almost no effect for East-born ones. Average wage gains for moves to the East tend to be smaller, consistent with the lower average wage level in the East.

The solid lines with diamonds plot the estimated wage gains for within-region job-to-job switches from regression (3) for workers in their home region.[23] We find that workers experience fairly large gains even moving jobs within-region, suggesting that they are climbing a job ladder in the presence of labor market frictions. These findings highlight that we need to benchmark the cross-regional wage changes with the within-region gains to properly infer the cost of moving between regions. Specifically, we need to take into account that workers moving between regions are selected: they are the ones that received job offers sufficiently appealing to make them migrate. Our model will allow us to do so structurally.

In Supplemental Appendix N, we list the full estimates from specification (3), and show that our results are robust to alternative definitions of job-to-job switches and migration.

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

[23]We omit the within-region wage gains of workers from the other region. They are extremely similar.

Burdett and Mortensen (1998) into a multi-region economy inhabited by heterogeneous firms and workers that are subject to different types of spatial frictions. The model is motivated by the empirical facts. First, the 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 spatial barriers, in particular, 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. Our model nests the standard spatial frictions used in the spatial literature in addition to labor market frictions.

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. We perform the analysis in steady state since the 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*, in an economy inhabited by a continuum of workers of types $i \in \mathbb{I}\{1, .., I\}$ with mass $\bar{D}^i$, where $\sum_{i \in \mathbb{I}} \bar{D}^i = 1$.[24] 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.[25] We normalize $P_c = 1$.

Workers and firms operate in a frictional and local 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. 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. Here, z_{jx}^i is the worker's relative search efficiency, which depends on the worker's current and destination locations (j, x) to capture that it may be easier to find job opportunities locally. Search efficiency also depends on the worker's type i, reflecting that it may be easier for workers to find open positions in their home location, for example due to reliance on social networks or referrals (as in, e.g., Galenianos (2013)). Search effort is subject to a cost,

[24] 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.

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

to be paid in 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 continuum of firms exogenously assigned to locations $j \in \mathbb{J}$, where M_j is the mass of firms in location j and $\sum_{j\in\mathbb{J}} M_j = 1$. 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 $[\underline{p}_j, \bar{p}_j] \subseteq \mathbb{R}^+$.[26] 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.

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 $M(\bar{a}_j, \bar{v}_j) = \bar{a}_j^{\chi}\bar{v}_j^{1-\chi}$. 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 can always separate from a match and engage in home production with a backyard technology that has productivity per efficiency unit given by R_j. Workers separate 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.

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 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.

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

Previous work with heterogeneous types (e.g. Moser and Engbom (2018)) assumes that the labor market is segmented by type. In our framework, each firm 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 the total number of workers, as in the standard Burdett-Mortensen framework. We provide details 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

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

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, as in, for example, Caliendo, Dvorkin, and Parro (2019), which capture shocks to workers' preferences for being in a specific location. These shocks simplify the model characterization and computation. We assume that workers operating the backyard technology are subject to the same shocks, which fixes a lower bound for wages in each location.

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

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

and the expected value of an offer is

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

Similarly, an unemployed worker of type i in location j receiving an offer w' from x solves

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

The probability of an unemployed worker accepting this offer is $\mu_{jx}^{U,i}\left(b_j^i,w'\right)$, defined analogously to the acceptance probability of employed workers. The expected value of an offer is

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

The discounted expected value of employment $W_j^i(w)$ of a worker i earning wage w in location j consists of the 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 $a_{jx}^i\left(s_x\right)\vartheta_x^{1-\chi}$, which is a function of the optimal search effort s_x, and a continuation value for separating into unemployment at rate δ_j^i

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

Similarly, the unemployment value is:

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

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

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

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

$$\pi_j(p) = \max_w (p-w) \sum_{i\in\mathbb{I}} \theta_j^i l_j^i(w), \tag{9}$$

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 by solving

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

where $\pi_j(p)$ are the maximized profits per vacancy from (9). 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 policy gives the total mass of offers posted in each location,

$$\bar{v}_j = \int_{\underline{p}_j}^{\bar{p}_j} v_j(p)\, \gamma_j(p)\, dp, \tag{11}$$

and the wage policy gives the endogenous distribution of offers

$$F_j(w) = \frac{1}{\bar{v}_j} \int_{\underline{p}_j}^{\hat{p}_j(w)} v_j(p)\, \gamma_j(p)\, dp, \tag{12}$$

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. We obtain the steady state value of $l_j^i(w)$ from its law of motion

$$\dot{l}_j^i(w) = \vartheta_j^{-\chi} \frac{\bar{a}_j^i}{\bar{a}_j} \mathcal{P}_j^i(w) - q_j^i(w)\, l_j^i(w) \qquad \text{if} \quad w \geq R_j, \tag{13}$$

and $\dot{l}^i_j(w) = 0$ if $w < R_j$. 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) $\frac{\bar{a}^i_j}{\bar{a}_j}$, the share of applications going towards location j that is filed by workers of type i; and iii) $\mathcal{P}^i_j(w) \in [0,1]$, 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,

$$\mathcal{P}^i_j(w) \equiv \frac{1}{\bar{a}^i_j} \sum_{x \in \mathbb{J}} \left[\int a^{E,i}_{xj}(w') \, \mu^{E,i}_{xj}(w', w) \, dE^i_x(w') + a^{U,i}_{xj}(b) \, \mu^{U,i}_{xj}(b, w) \, u^i_x \right]. \tag{14}$$

The second term in (13) is the separation rate, where

$$q^i_j(w) \equiv \delta^i_j + \sum_{x \in \mathbb{J}} \vartheta_x^{1-\chi} a^{E,i}_{jx}(w) \int \mu^{E,i}_{jx}(w, w') \, dF_x(w'), \tag{15}$$

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.

In steady state, the mass of workers per vacancy solves $\dot{l}^i_j(w) = 0$, and thus

$$l^i_j(w) = \frac{\mathcal{P}^i_j(w) \, \vartheta_j^{-\chi} \frac{\bar{a}^i_j}{\bar{a}_j}}{q^i_j(w)} \qquad \text{if } w \geq R_j \tag{16}$$

and zero otherwise.

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

$$E^i_j(w) = \int_{\underline{p}_j}^{\hat{p}_j(w)} l^i_j(w_j(z)) \, v_j(z) \, \gamma_j(z) \, dz, \tag{17}$$

where $l^i_j(w)$ is given by (16). The mass of unemployed workers is defined via the flow equation

$$\dot{u}^i_j = \delta^i_j e^i_j - \varphi^i_j u^i_j,$$

where φ^i_j is the rate at which workers leave unemployment, given by

$$\varphi^i_j = \sum_{x \in \mathbb{J}} \vartheta_x^{1-\chi} a^{U,i}_{jx}(b) \int \mu^{U,i}_{jx}(b, w') \, dF_x(w').$$

In steady state, the mass of unemployed workers is then

$$u_j^i \equiv \frac{\delta_j^i}{\varphi_j^i + \delta_j^i} \bar{D}_j^i, \tag{18}$$

where $\bar{D}_j^i \equiv e_j^i + u_j^i$.

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. The applications are 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, which are 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 using the figure 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. Matches and separations determine the employment distribution and unemployment in location j, which in turn determine output and hence the price level, at the top of the diagram.

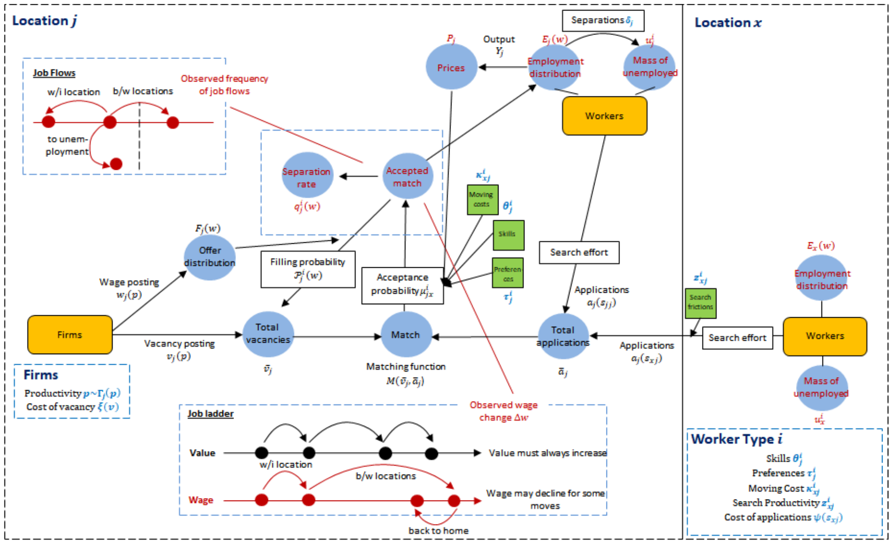
4.2 Stationary Equilibrium

As discussed, we focus on the steady state equilibrium of the economy, 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,* $\{F_j(w)\}_{j\in\mathbb{J}}$*;*

Figure 4: Illustration of the Model



Notes: The figure shows the main building blocks of the model. Yellow boxes are the model's agents. Blue circles are endogenous objects. We use red text to denote endogenous objects that are observable and black text to denote unobservable objects. Green squares are spatial frictions.

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, vacancy posting, and wage policies, according to equations (9), (11) and (12);*

4. *firm sizes and worker distributions satisfy the stationary equations (16), (17), and (18).*

Our model does not admit an analytical solution. However, the following proposition shows that the wage policies follow a system of differential equations, which facilitates significantly 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*

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

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

$$\tilde{q}^i_j(p) \equiv \delta^i_j + \sum_{x\in\mathbb{J}} \vartheta_x^{1-\chi} \tilde{a}^{E,i}_{jx}(p) \int \tilde{\mu}^{E,i}_{jx}(z,z')\, d\tilde{F}_x(z')$$
$$\tilde{\mathcal{P}}^i_j(p) \equiv \frac{1}{\bar{a}^i_j} \sum_{x\in\mathbb{J}} \left[\int \tilde{a}^{E,i}_{xj}(z')\, \tilde{\mu}^{E,i}_{xj}(z',z)\, d\tilde{E}^i_x(z') + a^{U,i}_{xj}(b)\, \tilde{\mu}^{U,i}_{xj}(b,p)\, u^i_x\right]$$

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

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

Proof. See Appendix D.2. □

Our framework is a generalization of the benchmark Burdett-Mortensen model (Mortensen (2005)). We show that our model collapses to the standard framework if we shut down the spatial heterogeneity in Appendix D.3.

5 Estimation

We now examine the effects of spatial frictions and labor market frictions on the allocation of workers to firms in general equilibrium. The model is estimated by simulated method of moments.

5.1 Identifying the Spatial Frictions

Our key challenge is to separately identify the spatial frictions ($\hat{\kappa}_{jx}$,τ^i_j, and z^i_{jx}) from the labor market frictions. Our identification strategy relies on the insight that the labor market frictions directly impact the allocation of labor within locations, and can therefore be identified from a rich set of within-location moments, using similar moments as is standard in the 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 the cross-location moments. While all model parameters are jointly identified, we next provide a heuristic argument for identifying the spatial frictions.

Moving Costs and Location Preferences: τ and κ. We can pin down these moments using the average wage gain conditional on a move for an individual of type i, employed in location j, and taking a job in location x[27]

$$\underbrace{\mathbb{E}\left[\log(w_x^i\theta_x^i)-\log(w_j^i\theta_j^i)\right]}_{\text{Average Observed Wage Gain}} = \underbrace{\log\left(\theta_x^i\right)-\log\left(\theta_j^i\right)}_{\text{Comparative Advantage}} + \tag{19}$$
$$\int\left(\int\underbrace{(\log w'-\log w)}_{\text{Wage Gain}}\underbrace{\frac{\mu_{jx}^{E,i}(w,w')}{\bar{\mu}_{jx}^{E,i}(w)}}_{\text{Rel. Prob. Accept}}\underbrace{\mathrm{d}F_x(w')}_{\text{Offers CDF}}\right)\underbrace{\frac{a_{jx}^{E,i}(w)}{\bar{a}_{jx}^{E,i}}\mathrm{d}E_j^i(w)}_{\text{Weighted Employment CDF}},$$

where $\bar{a}_{jx}^{E,i}\equiv\int a_{jx}^{E,i}(w)\,\mathrm{d}E_j^i(w)$ and $\bar{\mu}_{jx}^{i,E}(w)\equiv\int\mu_{jx}^{i,E}(w,w')\,\mathrm{d}F_x(w')$.

Given offer distributions $F_x(\cdot)$, employment distributions $E_j^i(w)$, and the share of applications coming from each firm $\frac{a_{jx}^{E,i}(w)}{\bar{a}_{jx}^{E,i}}$, which are all mostly shaped by labor market frictions, as well as an estimate of skills θ, the equation directly relates the moving costs κ and local preferences τ to the relative wage gains of cross-location movers. Consider the limiting case when $\sigma\to 0$. In that case, workers accept an offer if and only if $W_x^i(w')-\kappa_{jx}^i\geq W_j^i(w)$. Since the value functions are increasing, the cutoff wage level $\hat{w}_{jx}^i(w)$ at which an individual of type i employed in location j would accept an offer from location x is an increasing function of w. An increase in κ_{jx}^i, or a decrease in τ_x^i, would raise this cutoff wage for any level of w. As the worker accepts only relatively better offers, the expected wage gain of a move increases in κ_{jx}^i and decreases in τ_x^i.

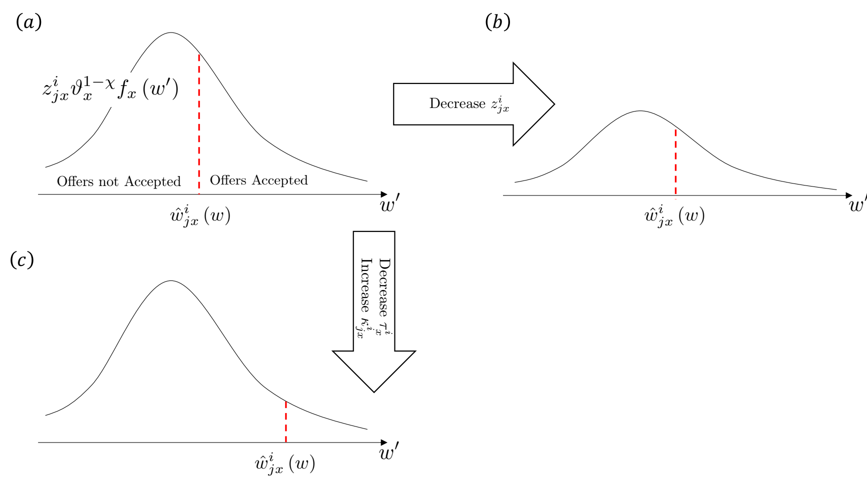
Without further restrictions, we cannot separate the moving costs from the location preference parameters. To separate the two, we assume that moving costs are identical for all worker types, reflecting for example relocation costs and transaction costs on the housing market. Under that assumption, the location preferences identified from the differences in wage gains for individuals of different types that make the same migration move.

Search Efficiency: z. Given an estimate of the labor market frictions, as well as estimates of skills, moving costs, and preferences $(\theta,\,\kappa,\,\tau)$, we can recover the relative search efficiencies from the relative job-to-job flows within and between locations. The rate at which workers of type i currently employed in location j move towards a job in location x is given by

$$\underbrace{\psi_{jx}^i}_{\text{Quit Rate}} = \left[\underbrace{\vartheta_x^{1-\chi}}_{\text{Tightness}}\underbrace{\bar{a}_{jx}^{E,i}}_{\text{Applications}}\right]\times\left[\int\left(\int\underbrace{\mu_{jx}^{E,i}(w,w')}_{\text{Prob. Accept}}\underbrace{\mathrm{d}F_x(w')}_{\text{Offer CDF}}\right)\underbrace{\frac{a_{jx}^{E,i}(w)}{\bar{a}_{jx}^{E,i}}\mathrm{d}E_j^i(w)}_{\text{Weighted Employment CDF}}\right] \tag{20}$$

[27]The flow utility of an individual i employed at a firm that pays wage w per efficiency unit in location j is given by $\frac{1}{P_j}\tau_j^i\theta_j^i w$. However, the observed nominal wage is simply $\theta_j^i w$, since τ_j^i does not enter into the wage.

Figure 5: Identifying Spatial Frictions



Notes: 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, $\vartheta^{1-\chi}_x z^i_{jx} f_x(w)$. Moving from panel (a) to panel (b) illustrates the effect of an increase in spatial search frictions (i.e. a decrease in z^i_{jx}) on the the distribution of accepted offers; moving from panel (a) to panel (b) illustrates the effect of either an increase in moving costs (κ^i_{jx}) or a decrease in preferences for the destination location $\left(\tau^i_x\right)$.

Since $\bar{a}^{E,i}_{jx} = z^i_{jx}\bar{s}^{E,i}_x$, where $\bar{s}^{E,i}_x \equiv \int s^{E,i}_{jx}(w)\, \mathrm{d}E^i_j(w)$, a lower search efficiency z^i_{jx} leads to lower job-job flows from location j to x, given the acceptance probability $\mu^{E,i}_{jx}(w, w')$, which is not directly affected by z^i_{jx} itself.

Figure 5 illustrates how the search efficiency, moving costs, and location preferences can be separetely identified. 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, $\vartheta^{1-\chi}_x z^i_{jx} f_x(w)$. The accepted offers, assuming again that $\sigma \to 0$, are at the right of $\hat{w}^i_{jx}(w)$, and hence the mass of job flows per unit of search effort is the integral under the wage offer density to the right of $\hat{w}^i_{jx}(w)$. Going from panel (a) to (b), a decrease in the search efficiency z^i_{jx} reduces the mass of offers received, and hence the worker flows. For comparison, 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). This shift changes the average wage gain. Since τ and κ also affect worker flows across locations, we need both flows and wage gains to separate the effect of the search efficiency from location preferences and moving costs.

Discussion of Identifying Assumptions. Our identification argument is based on two assumptions that are at the core 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 very limited effect on workers' wages (Jäger, Schoefer, Young, and Zweimüller (2020)) 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 what we infer as a lower skill level of a given type i could represent some type of discrimination from firms, rather than a lower level of human capital. Similarly, larger wage gains for movers between locations could be driven by firms offering wage premia to compensate workers that have to migrate to accept a job offer. 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 interpretation 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 in theory the model can be solved for a large number of locations, to estimate the model we need to match worker flows and wage gains between every pair of locations, as well as distributions in each location. To keep the number of moments at a reasonable level, we therefore limit 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. Appendix F provides further details. This number of locations and types allows us to distinguish the role of the former East-West border from more general spatial frictions. 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.[28] Firms' log productivity is drawn from a log-normal distribution with equal variance in all locations, Σ, and mean A_j. 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 $v_j(p) = \xi_{0,j} \left(\frac{\pi_j(p)}{\bar{\pi}_j(p)}\right)^{\frac{1}{\xi_1}}$. 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 $\xi_{0,E}$.

We fix the unemployment benefits b_j^i so that $U_j^i = W_j^i\left(w_j\left(\underline{p}_j\right)\right)$. Under this assumption our model collapses to the standard Burdett and Mortensen (1998) condition, $w_j\left(\underline{p}_j\right) = R_j$, once we remove preference shocks and spatial frictions.

Finally, we set the backyard technology to $R_j = \iota \underline{p}_j$, where $\iota \leq 1$ determines how profitable it is to set up a firm since R_j provides a lower bound on workers' wages.

Parametrizing Spatial Frictions. We interpret the moving cost as opportunity cost of foregone wages (Sjaastad (1962)), and assume that the moving cost of a given worker type is symmetric and proportional to her average value, $\kappa_{jx}^i = \hat{\kappa}_{jx} \bar{W}^i$, where $\bar{W}^i = \frac{1}{e^i} \sum_{j \in \mathbb{J}} \int W_j^i(w)\, dE_j^i(w)$ and $e^i \equiv \sum_{j \in \mathbb{J}} e_j^i$. Otherwise, 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.

We assume that $\hat{\kappa}_{jx}$ is a symmetric function of distance between locations j and x, identical for all workers,

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

The symmetry across worker types will be important for identification because it loads all asymmetries by type on the preference parameter τ_j^i.

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

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

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

[28] 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 $Prob_u = 1 - e^{-\delta}$.

home region, where $r(i)$ maps locations to regions. This specification allows individuals to value 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:

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

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, $\tau_{NE} = \tau_{SE} = \tau_E$. In our estimation below, we show 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. We provide more details in Appendix G. To set workers' relative productivity, θ^i_j (row 8), we use the fact that the model, due to wage posting, 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 the individual fixed effect is location-specific. We therefore estimate the modified AKM regression

$$\log(w_{it}) = \alpha_i + \psi_{J(i,t)} + \beta \mathbb{I}^{(h_i \neq R(J(i,t)))} + BX_{it} + \epsilon_{it}, \tag{21}$$

where, with a slight abuse of notation, 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 home region h_i is currently employed at a firm in the other region.[29] We show in Appendix E that β identifies the comparative advantage of workers in their home region, θ^i_i. We obtain workers' average skills, θ^i, from their average worker fixed effects, and find

[29] 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)).

Table 2: Calibrated Parameters

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

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.

$\beta = 0.019$, 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.

5.3 Moments

We are left with 21 parameters that we jointly estimate through simulated method of moments. We target overall 305 moments shown in Table 3, and provide further details on all the moments in Appendix G.

Choice of Moments. Based on our identification argument above, we target the 64 wage gains and job flows by type i, location j, and destination x to identify the spatial frictions (rows 1 and 2 of Table 3). Since the model is in steady state, the size of the spatial frictions together with firms' vacancy costs determine labor demand and supply in each location, and we therefore also target the distribution of employed and unemployed workers across locations and the firm component of wages in each location and for each type relative to $(i, j) = (NW, NW)$ (rows 3, 4 and 5). Overall, these moments help us to pin down the preferences $\left\{\tau_j^i\right\}$, search efficiencies $\left\{z_{jx}^i\right\}$, moving costs $\left\{\kappa_{jx}^i\right\}$, and vacancy costs $\{\xi_j\}$.

To estimate the labor market frictions, our model needs to be consistent with the joint

Table 3: Targeted Moments

	Moments	N	Source	Model Fit	Key Parameters
(1)	Wage gains of job-job moves, by (i, j, x)	64	Sect G.2.1	Fig 6	$\left\{\tau_j^i\right\}$; $\left\{\kappa_{jx}^i\right\}$
(2)	Frequency of job flows, by (i, j, x)	64	Sect G.2.2	Fig 6	$\left\{z_{jx}^i\right\}$; $\{\xi_j\}$
(3)	Employment shares, by (i, j)	16	Sect G.2.3	Fig A6	$\left\{\tau_j^i\right\}$; $\left\{z_{jx}^i\right\}$; $\{\xi_j\}$
(4)	Unemployment shares, by (i, j)	16	Sect G.2.4	Fig A6	$\left\{\tau_j^i\right\}$; $\left\{z_{jx}^i\right\}$; $\{\xi_j\}$
(5)	Firm component of wages, by (i, j)	15	Sect G.2.5	Fig A6	$\left\{\tau_j^i\right\}$; $\{Z_j\}$
(6)	Average firm component of wages, by j	3	Sect G.2.6	Fig A6	$\{Z_j\}$
(7)	Relative GDP per worker, by j	3	Sect G.2.7	Fig A6	$\{Z_j\}$
(8)	Unemployment rates, by j	4	Sect G.2.8	Fig A6	ν
(9)	Deciles of firm-size distributions, by j	40	Sect G.2.9	Fig A7	σ, ϵ, $\{\xi_j\}$
(10)	Slope of wage vs firm size relationship, by j	4	Sect G.2.10	Table A28 and Fig A8	Σ, $\{\xi_j\}$
(11)	Slope of J2J wage gain vs firm wage, by j	4	Sect G.2.11	Table A28 and Fig A8	σ, ϵ, Σ
(12)	Slope of separation rate vs firm wage, by j	4	Sect G.2.12	Table A28 and Fig A8	σ, ϵ
(13)	Std of job-job wage gains, by (i, j, x)	64	Sect G.2.13	Table A28 and Fig A9	σ, Σ
(14)	Profit to labor cost ratio, by j	4	Sect G.2.14	Table A28	ι

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.

distributions of firm wage and size, $G_j^i(w)$, in each location. We therefore target the share of employment in each decile of the firm size distribution (row 9) and the relationship between firm wage and size (row 10). These moments are relevant to discipline firms' vacancy costs $\{\xi_j\}$ since lower posting costs imply that more labor is concentrated at the most productive firms. The moments also help determine the variance of the firm productivity Σ since the variance of wages increases in Σ.

The variance of taste shocks σ governs how directed workers' moves are. As $\sigma \to \infty$, the idiosyncratic preference shocks dominate workers' acceptance decisions and workers become equally likely to accept offers that give a wage increase or decrease. The cost of search effort ϵ modulates the relationship between workers' search intensity and the value of employment at their current firm. When $\epsilon \to \infty$, workers search at equal intensity irrespective of their current job's value, while for any $\epsilon < \infty$ workers in low paying jobs search more intensively. To separately identify σ and ϵ, we target the relationship between workers' wage and their wage gains upon a job-to-job move (row 11), and the relationship between workers' separation rates (including job-to-job moves) and their wage (row 12). The former increases in σ, while the latter increases in ϵ.[30] We also target the standard deviation of the job-to-job wage gains by type i, current location j, and destination location x (row 13). A higher σ makes workers more likely to accept offers with a negative wage change.

[30]Both relationships are negative, hence when they increase, they become less steep.

The local unemployment rates (row 8) allow us to identify the relative search intensity from unemployment ν, given the separation rates that we calibrated directly.

The productivity shifters $\{A_j\}$ are mainly related to the relative average wage paid by firms in each location, since a higher productivity leads firms, everything else equal, to offer higher wages. A higher productivity is also reflected in a higher relative GDP per worker, which we target as well (rows 6 and 7).

Finally, the ratio of firms' profits to labor costs (row 14) helps us to pin down the productivity of the backyard technology ι. Since workers have the possibility to leave employment and get $\iota \underline{p}_j$, a larger ι implies that workers need to be compensated more and firms' profits are lower.

Computing Worker Flows. While our theory does not distinguish work and residence location to keep the model tractable, a sizable share of individuals in our data report to be working in a location different from their residence.[31] We therefore need to take a stand on how we define cross-location moves. 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 of the received offers lead workers to commute rather than migrate. On the other side, including all job-to-job moves regardless of residence could underestimate the frictions since commuters most likely do not pay the same fixed costs of relocating as migrants. To strike a balance, our baseline definition of a cross-location move includes all movers that change their work location and update their residence plus all cross-location moves that take the worker further away from her current residence as long as the worker's residence remains within 200km of her job.[32]

In Supplemental Appendix P, we re-estimate our model with a broader and a narrower definition of cross-location moves, respectively, and show that our results are consistent across alternatives.

Proposition 1 allows us to solve the model in just a few seconds despite its high dimensionality. We provide more details on our estimation algorithm in Appendix H.[33]

5.4 Model Fit

The model closely matches the key moments that help to identify the spatial frictions − the wage gains from job-to-job moves and the job flows. The left panel of Figure 6 plots the wage gains of job-to-job movers in the data against those in the model (from row 1 of Table 3).[34]

[31] About 7% of workers work in a location different from their residence.

[32] As mentioned in Section 2, the living location is self-reported and subject to misreporting. We therefore exclude individuals that report to be living far away from their job as it is likely that these observations are misreported.

[33] Figure A5 in the Appendix shows that all parameters seem to be properly estimated, at least based on the likelihood being locally single-peaked.

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

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 row 2). 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 take-aways. The model matches well the steady state distributions of workers and the average GDP, wages, and unemployment rates, consistent with the hypothesis that the German labor market is in 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.[35]

Overall, the model displays a good fit. 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.

5.5 Estimated Parameters

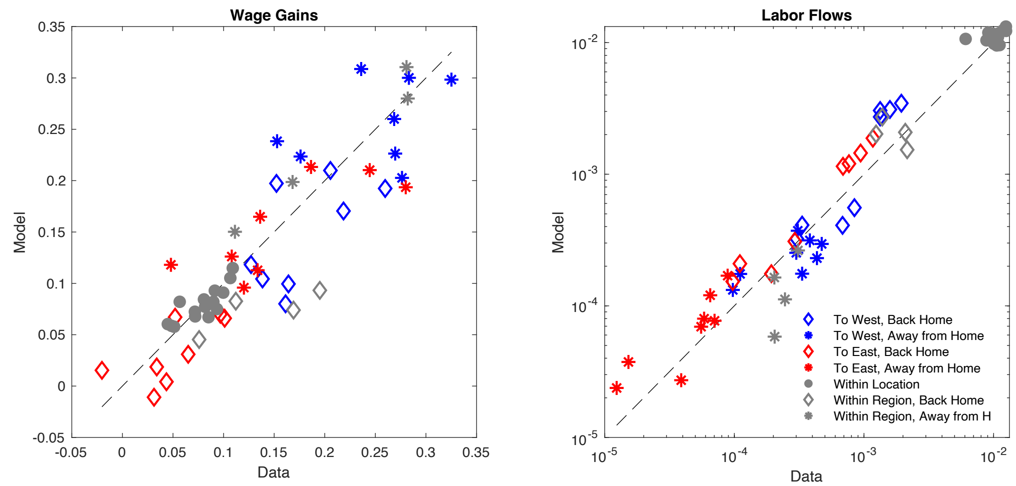
We present the estimated spatial frictions in Table 4, and discuss the remaining estimated parameters in Appendix H. Row (1) reports the estimated one-time moving costs as a fraction of the present discounted value of income, $\hat{\kappa}_{jx}$. Since these costs vary with distance, we present a range 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 €.[36]

Rows (2) and (3) show that a worker employed not in her home location but still in her

[35]In Figure A9, we show that adding individual fixed effects in wage growth brings the empirical estimates for the standard deviations of wage growths very close to the model's ones. In Figure A8 we show the non-parametric relationships for the moments in rows 10, 11, and 12 of Table 3.

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

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. Gray symbols are moves within-region, blue symbols are moves to the West, and red symbols are moves to the East. Diamonds symbolize cross-location moves within-region back to the home location (in gray) or cross-region moves back to the home region (blue or red). Stars symbolize cross-location moves within-region away from the home location (in gray) or cross-region moves away from the home region (blue or red). Gray circles are moves within-location.

home region would need to be paid, in real terms, about 7.4% more than in her home location to obtain the same utility. Moving away from both home location and region requires a yearly compensation almost 10% higher.[37]

Our estimated moving and preference costs are smaller than in Kennan and Walker (2011); Bryan and Morten (2019), due to the presence of labor market frictions, as in Schmutz and Sidibé (2018): 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. Second, we allow for cross-location search frictions, which reduces the size of the estimated moving costs. The magnitude of our estimated moving costs is similar to the findings in Schmutz and Sidibé (2018), who estimate moving costs between 13,700 € and 16,900 € between cities in France.[38]

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 (row 5). As before, we provide a range for searches between the two closest locations and between the two

[37]In Supplementary Appendix R, 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.

[38]Their costs are similar, though slightly lower than ours. The lower costs could arise because they consider moves between cities while we consider locations that are on average further apart.

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.

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 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 be for example due to social connections (Bailey, Farrell, Kuchler, and Stroebel (2020), Burchardi and Hassan (2013)).

6 Labor Misallocation across Firms and Regions

We next use the estimated model to study the role of spatial frictions in the allocation of labor across firms and regions. We find that spatial frictions have sizable aggregate and distributional effects, and that the aggregate effects, but not the distributional ones, are mainly driven by the allocation of labor within, rather than between regions. Importantly, we show that the aggregate gains are modulated by the way in which the labor market functions within regions.

While the quantitative results are necessarily specific to our context, the lessons we learn, and in particular the importance of the reallocation of labor within regions, generalize beyond the case of Germany.

6.1 Aggregate and Distributional Effects of Spatial Frictions

As a first exercise, we use the model to compute the effects of removing all the sources of spatial frictions. We recompute the equilibrium keeping all the parameters at their estimated values, but assuming that moving across locations is costless ($\kappa_0 = 0$), that there is no biased taste towards the home location or region ($\tau_l = \tau_r = 0$), and that workers have identical search productivity towards each location ($z_{l,1} = z_0 = 0$). We then compare the equilibrium with and without spatial frictions along five core statistics: i. GDP per capita; ii. average of workers' value functions of all employed and unemployed workers in the long-run steady state; iii. average wage of employed workers; iv. average wage per efficiency unit – i.e, the average wage that firms pay; and v. the share of the overall employment in West Germany.[39] The results from this exercise are included in the first column of Table 5, both for Germany overall, and separately for East/West Germany and for East/West Germans. While the model has four locations, we aggregate the results by region (East/West) as the heterogeneity across locations within regions is minimal. We next discuss a few take-aways.

Aggregate Effects of Spatial Frictions. We first focus on rows (1)-(5) of Table 5, which include the aggregate results for the whole Germany. Removing all spatial barrier leads to an increase in GDP, hence in labor productivity, of slightly less than 5%. Despite these relatively modest gains, the effect on worker's value is very large.[40] The reason is twofold. First, the decline in spatial frictions leads a larger increase in wages than in labor productivity since firms face stronger competition in the labor market, which leads to a reduction in their monopsonistic rents. Second, the reduction in spatial frictions directly increases the value of the problem since workers i) are not paying the moving cost κ each time they cross between locations; ii) are not paying the utility cost τ in the periods in which they live away from their birth-location; iii) have a higher continuation value due to the higher search productivity which reduces the effective cost of posting applications and improves their labor market prospects.

Finally, we notice that there is net reallocation towards East, hence towards the region with, on average, lower productivity. This result could seem counterintuitive at first, as in a neoclassical framework we would have expected a net labor reallocation towards the West. However, it is a direct implications of an inherent asymmetry in our frictional setting. In the data, and in our baseline estimation, there are fewer East Germans than West Germans, hence

[39] The difference between iii. and iv. is only due to the composition, in terms of skills θ, of the employed workers. For this reason, iii. and iv. are identical, by construction, when we compute it separately for East and West Germans (rows 16-17 and 21-22 of Table 5).

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

Table 5: Model Counterfactuals with Reduced Spatial Frictions

			All Frictions	w/i Locations	Partial Eq.	Technology	Preferences
			(1)	(2)	(3)	(4)	(5)
Overall	(1)	GDP 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)	Wage (per eff. unit)	+ 9.2 %	+ 11.4 %	- 1.7 %	+ 3.8 %	+ 1.8 %
	(5)	% in West	- 10.9 %	/	- 8.7 %	- 8.2 %	- 0.6 %
West	(6)	GDP 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)	Wage per eff. unit	+ 10.2 %	+ 10.5 %	+ 0.4 %	+ 5.6 %	+ 1.4 %
East	(10)	GDP pc	+ 17.0 %	+ 9.6 %	+ 10.0 %	+ 12 %	+ 4.5 %
	(11)	Value Function	+ 53.7 %	+ 46.2 %	+ 36.6 %	+ 39.1 %	+ 8.1 %
	(12)	Wage	+ 24.6 %	+ 16.6 %	+ 6.2 %	+ 13.3 %	+ 7.6 %
	(13)	Wage per eff. unit	+ 17.4 %	+ 16.6 %	+ 0.4 %	+ 7.1 %	+ 5 %
Born West	(14)	GDP pc	+ 1.9 %	+ 6.0 %	- 2.1 %	+ 0.3 %	- 0.4 %
	(15)	Value Function	+ 34.3 %	+ 34.5 %	+ 19.8 %	+ 23.2 %	+ 1.9 %
	(16)	Wage	+ 6.0 %	+ 10.6 %	- 5.0 %	+ 1.3 %	+ 0.3 %
	(17)	Wage per eff. unit	+ 6.0 %	+ 10.6 %	- 4.5 %	+ 1.3 %	+ 0.3 %
	(18)	% in West	- 27.3 %	/	- 25.1 %	- 23.2 %	- 6.8 %
Born East	(19)	GDP pc	+ 15.9 %	+ 8.7 %	+ 11.3	+ 12.1 %	+ 5.1 %
	(20)	Value Function	+ 47.2 %	+ 47.0 %	+ 30.5	+ 32.1 %	+ 6.6 %
	(21)	Wage	+ 23.1 %	+ 14.8 %	+ 10.4	+ 15 %	+ 8 %
	(22)	Wage per eff. unit	+ 23.1 %	+ 14.8 %	+ 10.8	+ 15 %	+ 8 %
	(23)	% in West	+ 43.5 %	/	+ 45.6	+ 41.4 %	+ 20.6 %

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)	GDP 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)	Wage (per eff. unit)	25.6 %	17.9 %	19 %	25.6 %	23.7 %	21.3 %
By Birth	(5)	GDP pc	26.4 %	11.2 %	23.4 %	11.2 %	13.1 %	19.7 %
	(6)	Value Function	18.7 %	8.3 %	8.5 %	9 %	10.7 %	13.4 %
	(7)	Wage	29.8 %	11.7 %	25.1 %	11.7 %	14.3 %	20.6 %
	(8)	Wage per eff. unit	18.1 %	1.7 %	13.8 %	1.8 %	4 %	9.7 %
	(9)	% in the West	71.1 %	0.3 %	71.1 %	0.4 %	6.6 %	43.8 %

more workers that have a strong attachment to the West than the East of Germany. As a result, shutting down the spatial frictions leads to a relatively larger positive labor supply shock in the East, as it is opening up to a larger labor market.[41]

Regional Differences. Focusing on Germany as a whole hides substantial heterogeneity, both across regions and across different group of workers. We first focus on the former: rows (6)-(9) and (10)-(13) include GDP per capita, values, wages and wages per efficiency units computed separately for the individuals living in the West and the East of Germany.[42]

The gains from removing spatial frictions are much larger in the East. There are two main reasons behind this result. The first one is mechanical. Despite similar observable characteristics, we estimated a large gap between East and West workers in unobservable human capital. As a result, as West workers move East and East workers move West, we would observe a reduction in the average human capital of the West workforce and an increase in the one of the East workforce. Given our estimates, this effect is quantitatively large in the East, as can be noticed by comparing the changes in wages and wages per efficiency units in the regions. The second reason is instead at the core of our economic mechanism, hence due to within-region

[41]In fact, this result is consistent with evidence from the initial phase of German reunification: while East Germans were way more likely to move West than viceversa, on net, there were almost as many male workers moving East than viceversa (Dauth, Lee, Findeisen, and Porzio (2019)).

[42]In the model, individuals move continously 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.

reallocation of labor and equilibrium forces. As we will explain in further details below, the reduction in spatial frictions leads to an increase in competive pressure which reallocates labor away from the lower productivity firms. This effect is stronger in the East since there is there a larger mass of firms with low productivity.

At the same time, also workers in West Germany benefits from a reduction in spatial barriers. It is relevant to contrast this result with the predictions of a neoclassical benchmark in which West Germany is inhabited by one representative high productivity firm and East Germany by one low productivity one. In that case, eliminating any barrier to labor mobility would lead to net flows of labor towards West until the marginal labor productivity is equalized. As a result, while overall labor productivity would increase, we would see an absolute *decline* of wage and labor productivity in the West, as the inflow of labor reduces its marginal product. This is not happening in our model, as there is a net reallocation towards East, as already pointed out, and an increase in productivity in the West due to an improvement in the within-region allocation of labor, as we discuss further below.

Differences by Birth-Place. While everyone benefits, East Germans see a larger increase in their labor productivity, wages, and values. This result is a reflection of the fact that, at baseline, East Germans are more likely to draw and accept offers from the lower productivity East. As we eliminate the source of attraction of East Germans towards East Germany, we see a very large net migration towards the higher productivity West. At the same time, West Germans are also more likely to move East. In fact, we simply observe a strong decline in sorting of individuals towards their birth-places. For West Germans, the net moves towards East lead them, on average, to work for lower productivity firms. Nonetheless, this effect is more than compensated from the equilibrium increase in average wage in both regions, and from the overall improvement in the allocation of labor. As a result, everyone benefits.

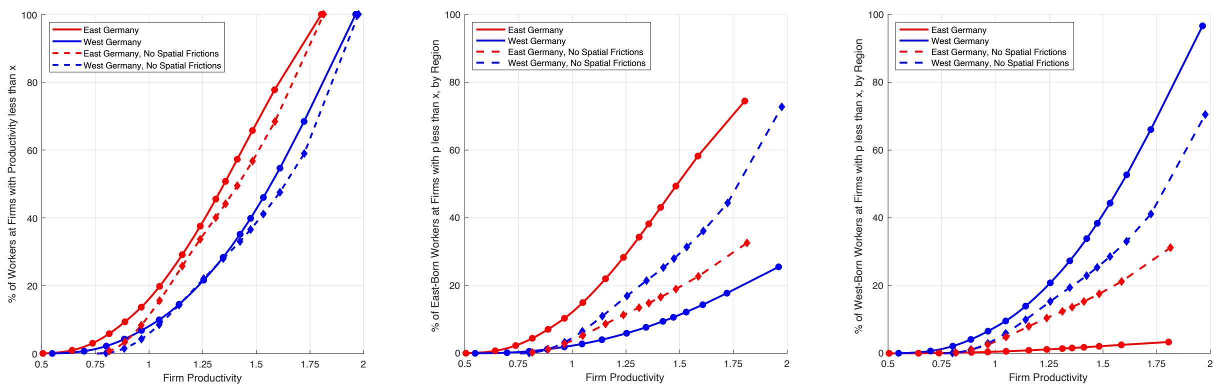
Implications for the West-East Gaps. Finally, in Table 6, we consider the implications for the gaps between regions and workers' birth-places. Column (1) includes the (large) baseline gaps between West and East Germany and Germans. Column (2) shows that, eliminating spatial frictions shrinks considerably the gaps across all dimensions. At the same time, it is not sufficient to completely eliminate them.

The regional gap remains due to the average higher productivity of firms in the West, the higher estimated amenity in the East and the presence of labor market frictions. The higher amenity in the East, allows firms there to still retain workers while paying a lower wage. However, it is not sufficient to explain the large residual wage gap.[43] The labor market frictions

[43]We estimate that $\tau_E = 1.110$, hence that each euro earned in the East values the equivalent of 1.11 euros earned in the West. Since the residual real wage gap is 17.9%, there is, even once we account for amenity differences, a roughly 7% higher wage in the West.

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 in the West. The right panel shows the same semi-CDF for West Germans.

shield low productivity firms from competition, allowing them to survive despite their lower offered wage. In the East, there are relatively more low productivity firms, hence a lower average wage and GDP per capita.

The remaining gap by birth-region is, instead, purely due to the estimated differences in their skills θ. Through the lens of our model, we find that West Germans, despite having similar observable characteristics, have higher (unobserved) skills. As a result, even in the absence of spatial frictions, West Germans earn a higher wage, produce more GDP per capita, and have higher value.[44]

6.2 Mechanism: the Key Role of Within-Region Labor Markets

Next, we shed more light on the mechanism behind the discussed aggregate effects. First, we show that the within-region allocation of labor plays a key role for the aggregate and regional effects, but less so for those by birth-place. Second, we discuss the importance of the equilibrium response of firms. Finally, we unpack the different sources of frictions, and highlight the interactions between them.

The Importance of the Within-Region allocation of Labor. Figure 7a shows, for both the baseline and the counterfactual with no spatial frictions, the CDFs of employment to firms of different productivity within East and West Germany. Assuming that wage is increasing in productivity, as is the case in our model, the baseline is consistent with the wage data shown in Figure 1b. While the CDF for West Germany lies to the right of the one for East

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

Germany, capturing the higher average productivity there, there is a lot of overlap between the two distributions as high productive firms in the East are more productive than the lower productivity ones in the West. This observation, in fact, has been motivating our focus as it implies that we could generate large aggregate gains in East Germany, by simply reallocating labor towards the more productive firms within the region.

Removing spatial frictions leads both distributions to shift to the right: labor reallocates towards the more productive firms. This effect is stronger in the East. At baseline, the presence of spatial frictions partially shields the low productivity firms in the East from competition through two margins: i. by reducing the value of unemployment, thus allowing firms to hire workers at a relatively low wage; ii. by limiting the rate at which workers are poached, as they are only rarely poached from firms in the West. At the same time, the spatial frictions also limit the ability of East firms to hire. Removing spatial frictions give them easier access to West workers, especially the unemployed ones, which would prefer to work at a low productivity firm than to stay unemployed. On net, the first effect dominates and the lowest productivity firms stop posting vacancies as they are not able to offer a higher value than unemployment.

To further unpack the drivers of the allocation of labor, it is useful to recall that the total labor employed at a firm of productivity p in region j is given by

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

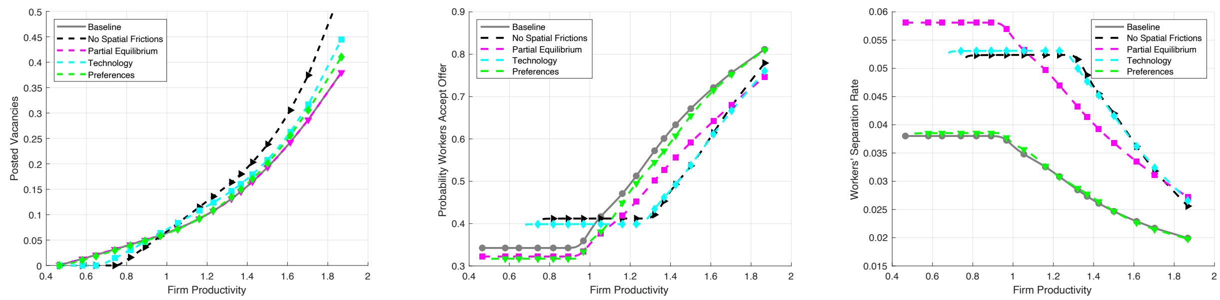
The first term captures the local market tightness and thus it only affects the allocation of labor between, but not within regions. The other three terms instead, could in principle explain the concentration of labor towards more productive firms. In the absence of spatial frictions, high productivity firms might post relative more vacancies (high $v_j(p)$), or they might be more able to attract workers upon meeting them (high $\mathcal{P}_j^i(w)$), or more able to retain them (low $q_j^i(w)$). In Figure 8, we plot these three objects as a function of firm productivity, for both the baseline economy and the counterfactuals. The number of posted vacancies is the main driver of the improvement in labor allocation. The separation rate also has a positive contribution: while all workers search more intensively, this effect is magnified at lower productivity firms. The acceptance probability, instead, mitigates slightly the reallocation gains, as workers are relatively more likely to accept offers at the lower productivity firms. This is driven by the fact that access to the country-wide pool of unemployed workers, previously noted, has a larger relative impact on the lower productivity firms.[45]

To quantify the role of the within region allocation of labor, the second column of Table 5 computes all the aggregate statistics keeping the within-location allocation of labor to firms

[45] 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: Unpacking the Emplo

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



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

and the firm wages as in the counterfactual without spatial frictions, but keeping constant the allocation of labor across locations as in the baseline. The results show that the overall gains in GDP and wages are even larger (since, as discussed, labor moves on net towards the lower productivity East). Yet, the gains are much smaller for East-Germany and for East-Germans, confirming that the reallocation across regions is important for the distributional effects of spatial frictions.

Large Equilibrium Effects. In the counterfactuals without spatial frictions, two sides of the market change their behavior relative to the baseline. Workers search more intensively even in further away regions, and they are more willing to move as they do not need to be compensated for the cost of moving or to live far away from their birth place. Firms react to the changed competition in the labor market by adjusting their posted wage and the number of opened vacancies. To unpack the separate role of each component, we compute the steady state of an economy in which firms wages and posted vacancies are kept constant at their baseline values, but workers are allowed to change their behavior in the absence of spatial frictions.

The results are shown in column (3) of Table 5. Comparing column (3) and column (1) makes it clear that the equilibrium effects operating through the change in firm behavior are crucial to generate the aggregate gains from spatial frictions. In fact, in the absence of equilibrium effect, the GDP per capita increases by only a mere 0.5% (row 1). This can also be seen in Figure 8: by construction, this partial equilibrium exercise does not vary posted vacancies, which, as argued, is the main driver of within-region allocation. Both the changes in the acceptance probability and the separation rate do contribute to improve the allocation of labor within region, but the effect is modest.

Lack of Opportunities or Unwillingness to Take them? The three types of estimated spatial frictions are very different in nature. The moving cost κ and the search productivity z are technological parameters that could be affected by policy. For example, a faster railway system or rental subsidies to facilitate the housing search could effectively decrease κ. An integrated online job portal could instead reduce z. These parameters also mainly represent lack of opportunities: an East born individuals simply has a hard time generating opportunities in the West because they are either too few, or not good enough to compensate for the cost of moving there. Instead, the taste parameter τ affects individual preferences and their willingness to take the available opportunities: even in the absence of spatial frictions generated by κ and z, East-Germans could still be predominantly working in East Germany as, everything else equal, they are more likely to accept offers received from their birth-region.

Given these differences, it is then natural to study the independent effect of each set of spatial frictions. We do so by recomputing the equilibrium of the economy when we remove either only the *technological* spatial frictions or the *preference* spatial frictions. The results, shown in columns (4) and (5) of Table 5, columns (5) and (6) of Table 6, and in Figure 8, show very strong complementarities between frictions. Removing each of these two types of frictions separately generates, on average, only about a quarter of the gains of removing both sources of frictions at the same time. As a result, any attempt to integrate the labor market would have a relatively limited effect if it does not tackle all sources of spatial frictions at once, which is especially a challenge since preferences are very hard to affect, as they are typically a slow moving object that changes across generations (Alesina and Fuchs-Schündeln (2007)).

6.3 The Local Labor Market Modulates the Aggregate Gains

We have shown that the aggregate impact of spatial frictions is mediated by their impact in misallocating labor across firms, even within region. As a result, we may expect that properly estimating the parameters of the labor market may be important to get a proper quantification of the aggregate impact of spatial frictions. We now verify this insight with a sensitivity exercise.

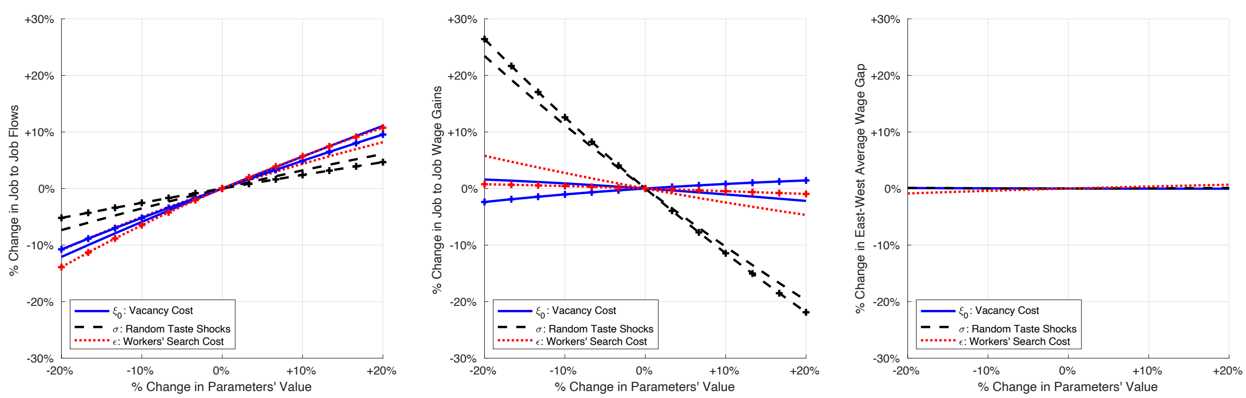
We vary, one at a time, three core parameters which modulate the strength of the labor market frictions, hence the local competition that firms face in the labor market: i. the vacancy cost (ξ_0), which affects the overall mass of vacancies posted by firms; ii. the variance of the preference taste shocks (σ), which affects the allocative power of wages since when σ is very large workers' acceptance decisions are purely driven by the preference shocks; iii. the elasticity of the workers search cost (ε), which modulates the ability of workers to move up the job ladder by searching heavily for better jobs while at the low rungs.

Figure 9 shows the effects of changing the three parameters on key targeted moments. In each case, we find that labor mobility is increasing in the size of the parameter. Instead, the impact on the wage gains of job to job moves is modest for the vacancy cost ξ_0 and the search cost ε, while large and negative for σ: as expect, when σ is large, workers moves are not directed by wages. Finally, we notice that changing either parameter has almost no effect on the aggregate wage gap between East and West Germany, consistent with the fact that these parameters mainly affect the distribution of labor within, rather than between, regions.

We then compute, just as in Section 6.1, the gains from removing spatial frictions starting from these economies with different labor market frictions. In Figure 10, we show the effect on GDP per capita, on workers' value functions, and on the wage gains of East Germans relative to the ones of West Germans. The aggregate gains in GDP per capita from removing spatial frictions are highly sensitive. Across the three parameters, we find that when labor mobility is higher at baseline, the aggregate gains are smaller. This result is intuitive and driven by the fact that higher labor mobility implies smaller potential gains from improving the within region allocation of labor. The impact of the spatial frictions on either the workers' value or the relative wage impact of East Germans is much less sensitive to the underlying value of the labor market friction parameters. This result is also intuitive. As we discussed, for these two statistics, the allocation of labor within region is less relevant: the value functions are affected by the removal of spatial frictions directly, while East Germans benefit more than West Germans because they gain access to the higher productivity West to which many end up moving.

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

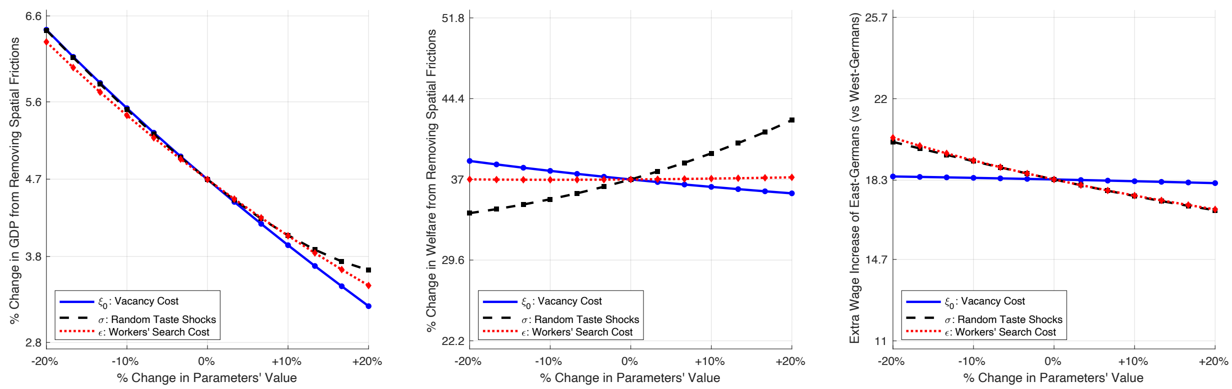
(a) Job Flows (b) Wage Gains (c) East-West Wage Gap



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.

Figure 10: Sensitivity of the Aggregate Effects to Labor Market Parameters

(a) GDP per Capita (b) Welfare (c) Wage Gains of East-Germans



Notes: We vary three different parameters modulating the labor market frictions 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. 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.

7 Conclusion

This paper has developed a quantitative labor market framework that encompasses frictional reallocation both across firms and across space to quantify the aggregate and distributional effects of spatial frictions. Bringing the model to matched employer-employee data from Germany, we learn three new insights that are relevant beyond our context. First, eliminating even large spatial frictions can have, as in our estimates, only modest effects on aggregate wages and productivity. Second, the aggregate effects of spatial frictions are mediated by their impact on the allocation of labor within regions across firms, which can dominate quantitatively. In fact, in our estimated economy with labor market frictions, the main effect of removing spatial frictions is to change the within-region allocation of labor, rather than generating net flows towards the high productivity region. Third, regional wage gaps and inequality of opportunities by birth region are not necessarily intertwined. Shutting down spatial frictions does not close the wage gap between East and West Germany, as labor market frictions are enough to shield low paying firms in the East from competition. However, it does substantially reduce the wage inequality between East and West-born individuals, as all workers now have equal access to jobs in all regions.

Overall, our analysis shows the importance of studying the labor allocation across firms and space in a unified framework. The model we build in this paper enables us to do so, and may prove helpful for future work on regional wage gaps and on the spatial and distributional consequences of policy interventions.

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