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Abstract

We develop a job ladder model with labor reallocation across firms and regions, and estimate it on matched employer-employee data to study the large and persistent real wage gap between East and West Germany. We find that the wage gap is mostly due to firms paying higher wages per efficiency unit in West Germany and quantify a rich set of frictions preventing worker reallocation across space and across firms. We find that three spatial barriers impede East Germans' ability to migrate West: migration costs, a preference to live in the East, and fewer job opportunities received from the West. The estimated model highlights that the spatial barriers needed to generate the large wage gap between East and West are small relative to the frictions preventing the reallocation of labor across firms. Therefore, policies that directly promote regional integration lead to smaller aggregate benefits than equally costly hiring subsidies within region.

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1 Introduction

Even within countries, large differences in wages and labor productivity across regions persist for decades.[1] Examples are the case of the Italian Mezzogiorno, Andalusia in Spain, and the East of Germany. These regional differences lead to three questions: first, are some locations inherently more productive, or are the workers in those locations more skilled? Second, if there is a causal effect of location on individual labor productivity and wage, why do people not migrate to take advantage of better opportunities? And finally, what are the aggregate costs of the barriers that prevent migration?

In this paper, we revisit these three questions through the lens of a job-ladder model with reallocation across firms and space, which we bring to matched employer-employee data from Germany. Germany is a natural setting since it exhibits a persistent 26% wage gap, in real terms, between East and West Germany, which is sharply delineated by the former border, as shown in Figure 1.

First, we show that location matters: more than 60% of the East-West wage gap is due to regional characteristics rather than worker composition, with labor being paid significantly more in the West.

Second, interpreting the data through the lens of our job-ladder model, we quantify three barriers that prevent the full integration of the East and the West German labor markets: workers face a one-time cost to move across regions, have a preference for their home region, and receive more job opportunities from home. We find that these spatial barriers, while sizable, are significantly smaller than previous estimates in the literature, since workers' low mobility and large wage gains when moving across space are partially the result of general labor market frictions that also operate within region.

Third, our estimates imply that the aggregate benefits from removing the spatial barriers are modest, and, in welfare terms, inferior to subsidies that improve the hiring of workers within region. For example, fully subsidizing workers' migration costs would increase the average wage by less than 0.5% and leave average utility unchanged since workers more frequently live away from their home region, which they dislike. On the other hand, providing an equally costly subsidy to firms to post more vacancies would improve the matching market in workers' home region and thus raise average welfare.

Both matched employer-employee data and a search model with labor reallocation across firms are crucial for our analysis. On the one hand, matched data enable us to control for unobserved heterogeneity across workers. This feature allows us to isolate the part of the wage gap that is due to regional characteristics rather than sorting. Moreover, since we can track workers' employers and locations over time due to the panel nature of the data, we can benchmark moves across space against moves across firms within the same location, and thus separate the part of the wage gain that is due to the spatial move from the part that is due to the worker's movement up the job ladder. On the other hand, the structure of our model, once brought to our data, allows us to separately estimate workers' home region preferences and migration costs. These have different aggregate implications: while preferences for the home region affect workers' location choice and regional GDP in the long run by drawing workers back to their home region, migration frictions worsen the allocation of workers to

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[1]Moretti (2011), Gollin, Lagakos, and Waugh (2014), Redding and Rossi-Hansberg (2017).

Figure 1: Average Real Daily Wage, 2009-2014

■	100.43
■	84.2
■	69.77
■	55.35
□	No Data
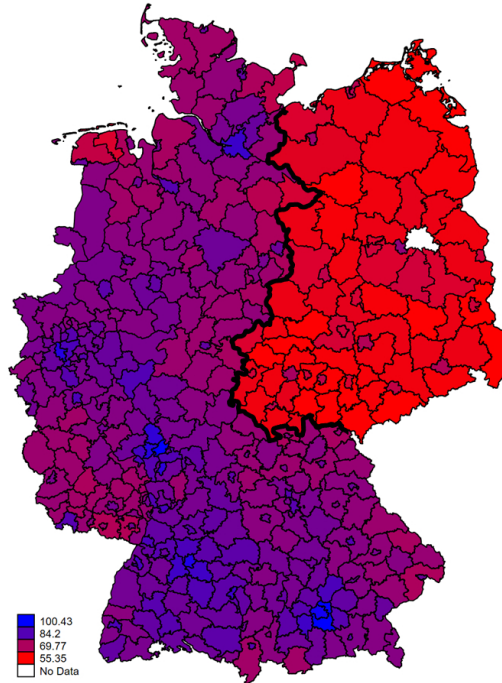
Notes: Average daily wages are obtained from a 50% random sample of establishments via the Establishment History Panel (BHP) of the Institute for Employment Research (IAB). Real wages are expressed in 2007 euros valued in Bonn, the former capital of West Germany, using county-specific prices from the Federal Institute for Building, Urban Affairs and Spatial Development (BBSR) in 2007, which are written forward in time using state-level price deflators from the Statistical Offices of the States. Former East-West border is drawn in black for clarification; there is no border today. We exclude Berlin since we cannot assign it unambiguously to "East" or "West", as we explain below.

firms by impeding workers' ability to climb a country-wide job ladder. In addition, we can separate the lack of opportunities to migrate, or the number of offers received, from the cost of migration, which affects the share of offers that are accepted.

Our paper consists of three main sections. We begin by documenting three stylized facts about the regional wage gap. We then develop a model with worker reallocation across space and across firms to interpret our findings. Finally, we estimate the model and use it to perform several counterfactuals.

Our empirical work combines two administrative datasets from the German Federal Employment Agency. We rely on matched employer-employee data from the Linked Employer-Employee Dataset (LIAB), which enables us to track the complete employment history of 1.9 million individuals for the period 1993-2014 together with the identifiers of the establishments for which these individuals work. Our second dataset is establishment-level data for half of all establishments in Germany from the Establishment History Panel (BHP), which we use to compute establishment-level moments.

We document three stylized facts. First, the real wage gap between East and West Germany is persistent and not driven by observables such as industry, education, or gender differences. Second, all workers obtain large wage gains when moving from East to West, suggesting that the wage gap is also not driven by sorting on unobservable ability. Furthermore, these gains are asymmetric and depend

on worker's home region: East-born workers obtain significantly higher average wage gains than West-born ones when making a move from East to West, while West-born workers obtain relatively higher wage gains when moving East. The asymmetry suggests that workers need to be compensated to leave their home region. Third, we show that mobility of workers across regions is in fact substantial, which implies that moving costs could be small. However, even conditional on distance and current location, workers are relatively more likely to move towards their home region, raising the possibility that they receive more job opportunities from there.

We develop a model to interpret our findings. Our framework combines two classes of models: a job-posting model à la Burdett-Mortensen (e.g., Burdett and Mortensen (1998)), in which workers move between heterogeneous firms subject to labor market frictions, and a model of worker mobility across space, along the lines of recent work in the trade and macro literature (e.g., Caliendo, Dvorkin, and Parro (2019); Bryan and Morten (2019)). Our theory allows for an arbitrary number of locations, characterized by an exogenous productivity distribution of firms, and an arbitrary number of worker types, characterized by differences in skills, preferences, and opportunities to move. Firms choose the wage to post and decide how many job vacancies to open. Workers randomly receive offers and accept an offer if it yields a higher present discounted value, moving across firms both within and across regions. Each firm posts a wage rate per efficiency unit of labor, which endogenously affects the composition of hires via the workers' acceptance probability. We derive a tractable solution represented by a system of two sets of differential equations with endogenous boundary conditions. To our knowledge, we develop the first general equilibrium model that encompasses, within a unified framework, frictional labor reallocation both across regions and across heterogenous firms.

We use the model together with matched employer-employee data to understand the origins of the spatial wage gap and to quantify the importance of the different spatial frictions supporting it. First, the model delivers an AKM-type regression (Abowd, Kramarz, and Margolis (1999)), which allows us to separate the contributions to the spatial wage gap of the average skills of East- and West-born workers, workers' comparative advantages in the two regions, and differences in establishment productivity. Second, the model shows that workers' wage gains from job-to-job switches and workers' flows across jobs can be used to identify workers' preferences for a given region, their opportunities to move, and the migration cost. Specifically, if the migration cost is symmetric and identical for all worker types, as is common in economic geography models, then workers' preferences for a given region can be identified by comparing the wage gains of East- and West-born workers making the same job switch across regions. On the other hand, the migration cost is identified from the average wage gains of workers that move between East and West Germany, relative to the average wage gains of workers that move within region. Finally, given the structure of the model, any remaining deviation in the flows of workers between regions from the model-implied flows must be due to differences in opportunities – i.e. in the number of job offers received.

Our estimated AKM regression shows that East-born workers are paid a 12% lower wage than West-born ones even within the same establishment, accounting for nearly 40% of the East-West wage gap. The remaining wage differential is due to a higher average establishment component in the West.

In other words, workers' location matters, raising the question of what barriers prevent East German workers from migrating West. We do not find any role for comparative advantage, but show that migration costs, workers' preferences, and opportunities to move all play a role in sustaining the wage gap. First, workers have a preference for their home region: individuals value one dollar earned while working away from their home region as 95 cents earned at home. This wedge amounts to a yearly cost of approximately €1,500. Workers also receive most of their job offers from the region in which they are currently working, and are more likely to receive an offer from their home region irrespective of their current location. For example, an East-born individual working in the East receives less than one in twenty job offers from the West. Finally, moving between regions entails a one time cost equal to 3.4% of an individual's life-time earnings, or approximately €17,000. The estimated barriers are significantly smaller than previous estimates in the literature.[2]

We use the model to study the aggregate implications of the different types of spatial frictions. A key finding of our paper is that even completely eliminating the migration cost between regions has only a minor effect on aggregate GDP and wages (which increase by less than 0.5%), and almost no effect on the spatial wage gap, despite the large differences between East and West Germany. This finding depends crucially on our interpretation of the data as a frictional labor market. By benchmarking workers' wage gains from cross-region moves to their wage gains from within-region moves, we estimate relatively small migration costs because, even though workers obtain on average large wage gains when moving between regions, a substantial part of this increase is due to workers' movement up the job ladder rather than the spatial component of the move. While in principle even a small migration cost could lead to sizable aggregate losses if it prevented many marginal workers from moving to a higher productivity region, our model shows that, in practice, it has only a modest effect. The reason is that the estimated productivity heterogeneity across firms within a region swamps the average productivity gap between East and West. Finally, due to the relatively large utility cost of working away from home, removing the migration cost does not increase aggregate welfare. The small increase in aggregate GDP and wages is completely offset by the utility cost of having more workers located away from home. While we find somewhat larger welfare gains associated with making East and West Germans equally likely to receive job offers from both regions, it could be difficult for a government to implement this policy given that workers often find jobs through referrals and local networks (e.g., Galenianos (2013)).

To further investigate the roles played by frictions that prevent the reallocation of labor within versus across regions, we examine two policies targeted to foster regional integration: a subsidy to the migration cost and a policy that posts additional vacancies in such a way that East and West Germans are equally likely to receive job offers from a given region. We compare these policies to two equally costly alternatives that improve worker reallocation within a given region, but do not promote better integration. We find that these latter policies deliver slightly smaller increases in the average wage and

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[2]For example, Kennan and Walker (2011) find, examining inter-state migration of white males in the United States, that the moving cost for the average mover is $310,000 (rather than €17,000 for moves between East and West Germany in our work) and that the home premium corresponds to an yearly wage increase of $23,000 (rather than €1,500).

in aggregate GDP, but provide larger welfare gains to the average worker since he obtains higher wages without the need to relocate. We therefore conclude that, in the context of Germany, policies aimed at promoting more migration are dominated in utility terms by policies that facilitate the reallocation of labor within a given labor market.

Our work yields three general insights that hold beyond the specific case of Germany. First, we show that a large regional wage gap can be supported in equilibrium by relatively small migration frictions, given a frictional labor market and productivity differences across regions. Second, we argue that it is important to distinguish between different types of spatial frictions to properly design labor market policies. If workers have strong home-region preferences, subsidizing worker mobility may improve aggregate GDP, but may come at a sizeable utility cost. As a result, untargeted hiring subsidies may provide larger welfare gains than policies promoting migration. Finally, we argue that it cannot be concluded from a lack of flows across regions that the labor market is not integrated. In the example of Germany, workers in fact receive quite a few job offers from the other region. However, they choose not to accept many of them.

In the final part of the paper, we shed further light on the mechanism driving the documented attachment of individuals to their home region. We find that individuals are more likely to move back to their home region after the birth of a child, indicating that they may seek help with childcare from family members. Moreover, we show that East workers moving to the West are more likely to move to counties that already host a large number of East individuals, consistent with the literature emphasizing the importance of ethnic enclaves (e.g. Edin, Fredriksson, and Åslund (2003)). Finally, we show that, in addition to their attachment to their home region, individuals display an attachment towards their home state within a given region. This finding suggests that our results are not driven by the historical separation of East and West Germany, but are applicable more generally.

Literature.   Our paper is motivated by and contributes to several strands of literature.

First, we provide a new framework to interpret and refine the results of a recent literature that has studied spatial wage gaps with panel data. This literature has pointed out that spatial sorting plays an important role in accounting for spatial wage gaps and that it is necessary to use panel data to properly quantify the degree of sorting (see Combes, Duranton, and Gobillon (2008), Hicks, Kleemans, Li, and Miguel (2017) and Alvarez (2018)).[3] In our context, we confirm these results, but, importantly, we highlight that interpreting the data without a frictional theoretical framework, as done in the cited literature, could lead to misleading results. Specifically, in our setting the wages of East-born workers increase steeply when moving West, which the existing literature would interpret as evidence of a large causal effect of working in the West. This interpretation does not take into account, however, that all job movers are selected − they must have received a good enough job offer to move. Once we control for this channel through our model, we conclude that, in fact, the causal effect of working in the West

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[3]Several other papers have documented, using a combination of different methods, the importance of sorting to explain wage gaps, e.g., Young (2013), Lagakos and Waugh (2013).

is much smaller than the one implied by an a-theoretical interpretation of the data.

Second, we show that using matched employer-employee data, interpreted through the lens of a frictional labor market model, can change some of the conclusions obtained by the quantitative literature on labor mobility across space or sectors, such as Artuç, Chaudhuri, and McLaren (2010), Kennan and Walker (2011), Caliendo, Opromolla, Parro, and Sforza (2017), Bryan and Morten (2019), or Caliendo, Dvorkin, and Parro (2019). These papers use the observed worker flows and average wage differentials across space or sectors to estimate the size of the mobility costs. Since worker flows in response to average wage gaps are relatively modest, the papers infer large migration costs or sizable compensating disamenities. We develop a frictional labor market theory that encompasses both worker mobility across space and across heterogeneous firms, building on the canonical model by Burdett and Mortensen (1998). This framework allows us to benchmark the size of spatial frictions to labor reallocation frictions, thus accounting for mover selection. Moreover, using cross-region flows of workers relative to within-region flows, we also separately identify the rate with which workers have an opportunity to move to the other region. Since we estimate that workers only rarely have opportunity to migrate, not taking this particular friction into account would lead to a severe overestimation of migration costs.

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 and from other locations. Consistent with our work, they estimate small migration costs. However, due to the assumption of homogenous labor, their paper cannot distinguish between migration costs and home bias, and due to the partial equilibrium assumption it cannot study the aggregate 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 sector in Brazil. In both of these papers, workers receive 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 contrast, in our model workers' probability of receiving and accepting offers depends on their identity and their current location. In particular, there is a mass of unemployed workers of both types in both regions. As a result, a small wage change can allow firms to attract another type of worker, which makes our wage functions discontinuous in principle. We resolve this problem by introducing extreme value shocks into the job ladder model, which smooth out the wage function, building on earlier insights to obtain tractable solutions for discrete choice problems from the trade literature (e.g., Eaton and Kortum (2002)).[4]

Last, our work is related to the literature that has examined East German convergence (or the lack thereof) after the reunification (e.g., Burda and Hunt (2001), Burda (2006)). This literature has

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[4]Another related paper is Hoffmann and Shi (2016). They theoretically analyze a two-sector Burdett-Mortensen model and provide the conditions under which this model admits an analytical solution, but do not allow for mobility frictions or estimate the model.

in particular studied possible drivers behind the wage gap between East and West Germany 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 as exogenously given the distribution of firms in each region and do not explicitly model the source of the productivity differences across regions. Instead, we use matched employer-employee data to estimate the roles of various migration frictions in a unified framework.

Our paper proceeds as follows. In Section 2, we describe our data. We then present three stylized facts on the East-West wage gap and worker mobility in Section 3. Section 4 introduces our model. We estimate the model and quantify the size of the spatial frictions in Section 5. Section 6 provides some additional interpretation of workers' preference for their home region. Section 7 concludes.

2   Data

We use four distinct datasets. First, we use establishment-level micro data from the Establishment History Panel (BHP), which are provided by the German Federal Employment Agency (BA) via the Institute for Employment Research (IAB). This dataset is a panel containing a 50% random sample of all establishments in Germany with at least one employee liable to social security on the 30th June of a given year, excluding government employees and the self-employed. The data are based on mandatory social security filings. Each establishment in the BHP is defined as a company's unit operating in a distinct county and industry.[5] For simplicity, we will refer to these units as "firms" throughout the rest of this paper. For each such unit, the dataset contains information on location, number of employees, employee structure by education, age, and occupation, and the wage structure in each year. The data are recorded since 1975 for West Germany and since 1992 for East Germany, and cover about 1.3 million establishments per year in the recent period.

Our second, and most important, dataset is matched employer-employee data from the longitudinal version of the Linked Employer-Employee Dataset (LIAB). The LIAB data contain records for more than 1.9 million individuals drawn from the Integrated Employment Biographies (IEB) of the IAB, which cover employment and socioeconomic characteristics of all individuals that were employed subject to social security or received social security benefits since 1993. These data are linked to information about approximately 400,000 establishments 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. Each observation is an employment or unemployment spell, with exact beginning and end dates within a given year. A new spell is recorded each time an individual's

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[5]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)).

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. Variables include the worker's establishment's location at the county level, the worker's daily wage, education, year of birth, and occupation. The data also contain the county of residence of the individual, since 1999. In contrast to the other variables, which are newly reported at each spell, the location of residence is only collected, for employed workers, at the end of each year and then added to all observations of that year, while for unemployed workers it is collected at the beginning of an unemployment spell.

The third dataset used is the German Socio-Economic Panel (SOEP), a longitudinal annual survey of around 30,000 individuals in Germany since 1984. The SOEP provides information about an individual's employment, family, living conditions, and education history. We will use the SOEP information to provide further evidence on the impact of an individual's birth location on labor market outcomes. The birth location is available for two subsamples of the SOEP. First, the wave of individuals in the SOEP drawn in 1984 covered only West German individuals, while a wave in 1990 covered only East German individuals. For these waves the birth location is known with certainty. We will refer to individuals from these waves that are still in the labor force in 2009-2014 as the "Old SOEP Sample". Second, for individuals that entered the survey while they were still in their childhood, the data contain information on the location of individuals' preschool, primary school, or secondary school. We will assume that the earliest schooling location is identical to an individual's birth location, and refer to these individuals who began high-school after the reunification as the "Young SOEP Sample".

Our fourth dataset is information on cost of living differences across German counties from the Federal Institute for Building, Urban Affairs and Spatial Development (BBSR (2009)). The BBSR conducted a study assessing regional price variation in 2007 across 393 German micro regions covering all of Germany that correspond to counties or slightly larger unions of counties.[6] The data cover about two thirds of the consumption basket, including housing rents, food, durables, holidays, and utilities. Figure 15a in Appendix E shows the map of county-level price levels. East Germany has a 7% lower population-weighted average price level.

Our core period of analysis is 2009 to 2014, the last year available in the IAB data, to focus on persistent differences between East and West Germany. For some empirical specifications that require a longer sample, we use the years 2004 to 2014. We adjust all wages based on the BBSR's local price index in 2007, and deflate wages forward and backward in time using state-specific GDP deflators from the statistics offices of the German states. We use industries at the 3-digit WZ93 classification, and apply the concordance by Eberle, Jacobebbinghaus, Ludsteck, and Witter (2011) to obtain time-consistent codes. All our analyses use full-time workers only, and exclude Berlin, which cannot be unambiguously assigned to East or West since it was divided between the two.

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[6]https://www.bbsr.bund.de/BBSR/DE/Veroeffentlichungen/Abgeschlossen/Berichte/2009_2010/Bd30RegPreisindex.html

Figure 2: East-West Real Wage Gap
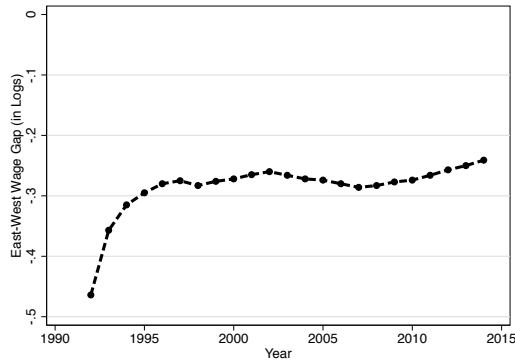
Source: BHP. Figure plots the time series of the coefficient in specification (1) obtained by regressing establishment-level wages on an indicator for East Germany without controls, where establishments are weighted by size.

3 Empirical Evidence of the Enduring Divide

We next document three facts on the German labor market. Fact 1 shows that there is a persistent real wage gap between East and West Germany which is not driven by observables such as industry, education, or gender differences. Three classic hypotheses have been formulated by the literature to explain such real wage gaps: (i) wages are higher in one region due to higher unobserved ability of workers and spatial sorting, (ii) wages are higher in one region as compensation for disamenities, and (iii) mobility barriers prevent reallocation.[7] Facts 2 and 3 show that, in our context, each one of these explanations is, at best, incomplete. Fact 2 documents that workers obtain large wage gains when moving from East to West, thus suggesting that a simple sorting explanation is not at play. Furthermore, these wage gains are asymmetric across East and West Germans, and thus unlikely to be the reflection of some general lower amenity of working in the West. Fact 3 shows that workers move frequently across regions, but their flows are relatively directed towards their home region. Therefore, a simple migration cost explanation is also not appealing. Instead, the results suggest that individuals could have a skill advantage, preferences, or better job opportunities in their home region.

Fact 1: Persistent Wage Gap, not due to Observables

We first show that a sizable and persistent real wage gap remains between East and West Germany, despite the absence of a physical or legal border, or language difference, since the reunification in 1990.[8] This wage gap is not driven by observables. Figure 1 plots the average daily wage from the BHP, adjusted for cost-of-living differences from the BBSR survey, for each county in Germany.[9] The large wage gap is not driven by a few outlier counties: Figure 16 in Appendix E shows that close

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[7]Without the scope to survey the literature, some references where each hypothesis is central are as follows: i) Combes, Duranton, and Gobillon (2008); Gollin, Lagakos, and Waugh (2014); Hicks, Kleemans, Li, and Miguel (2017); ii) Brueckner, Thisse, and Zenou (1999); Diamond (2016); Lagakos, Mobarak, and Waugh (2018); iii) Kennan and Walker (2011); Bryan and Morten (2019); Diamond, McQuade, and Qian (2019).

[8]Appendix A provides a brief discussion of the reunification process.

[9]Figure 15b in Appendix E shows that there is also a sharp difference in unemployment across the two regions.

to 80% of the West German population lives in counties with a higher average real wage than the highest-paying county in the East.

To formally establish the size and persistence of the regional wage gap, we run, in the BHP, an establishment-level regression of the form

$$\bar{w}_{jt} = \gamma \mathbb{I}_{j,East} + BX_{jt} + \delta_t + \epsilon_{jt}, \tag{1}$$

where $\bar{w}_{jt}$ is the average real wage paid by establishment j in year t, $\mathbb{I}_{j,East}$ is a dummy for whether establishment j is located in the East, X_{jt} is a vector of controls, and δ_t are time fixed effects. We weight by establishment size since we are interested in the average wage gap in Germany.[10] In the first step, we confirm the persistence of the real wage gap by running regression (1) without controls or time fixed effects separately for each year in the data, and plot the resulting time series of coefficients γ_t in Figure 2. We find that the real wage gap has been closing very slowly since the mid-1990s, and remains at around 25%.[11]

We next pool the data for our core sample period (2009-2014) and add successively more controls to show that the wage gap is not driven by observable worker characteristics or industry heterogeneity. Table 1 presents the estimates for γ. Column (1) shows that the unconditional wage gap for our core period is 26%. In column (2), we additionally control for the establishment's average share of male workers and the share of workers with a college degree, and in column (3) we further add controls for the share of workers that are older than 55 and the share of workers that are younger than 30, as well as the log of establishment size. With these controls the gap narrows slightly to 25%. Finally, column (4) includes 3-digit industry fixed effects to control for differences in industry structure, which narrows the gap slightly further. Overall, about 80% of the real wage gap is not explained by these observables. We provide more information on the college, gender, and industry controls in Figures 17a-18b and 19 in Appendix E, where we show that the share of college educated individuals is very similar in East and West, that the wage gap exists broadly and is roughly constant across all industries, and that the wage gap holds across counties with different gender composition or education. Appendix B.2 highlights that there is no clear gap in the average tax rate between East and West Germany.

Fact 2: Large but Asymmetric Wage Gains of Moves from East to West

We next study the wage gains of workers that move across regions.

For this analysis and for the remainder of the paper, we assign individuals to a "home region", either East or West Germany, and compare individuals with different home regions in 2009-2014. Since the social security data only provide labor market information, we classify individuals as East (West) German if at the first time they appear in our entire dataset since 1993, either employed or unemployed, their location of residence is in the East (West). Since the residence location is unavailable prior to

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[10]Table 10 in Appendix F provides the unweighted estimates.

[11]In Appendix B.1 we use aggregate data on GDP to perform a growth accounting exercise to show that most of the sizable GDP gap between East and West Germany today is due to TFP differences.

Table 1: Effect of Region on Real Wage

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

Notes: Table presents the regression results for the period 2009-2014. $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the establishment-level.

1999, we use the workers' first job's establishment location for those years.

We use survey data from the SOEP to validate our measure of an individual's home region. In the first step, we impute a home region in the "Old SOEP Sample", as previously defined, in the same way as in the LIAB and compare it to workers' birth region in the survey. As shown in Table 11 in Appendix F, we find that the imputed home region corresponds to workers' true birth region for 88% of workers born in East Germany and 99% of workers born in the West. In the "Young SOEP Sample", the imputed home region matches the region in which we observe the earliest non-tertiary schooling for an individual in 92% and 99% of cases, respectively. As a second step, we compare the wage gap in the SOEP between individuals classified as East and West German under our imputation to the wage gap calculated with the true birth/schooling region. In Appendix F, Table 12 shows that the wage gap is similar under both definitions. Thus, we find no evidence that our misclassification of some workers quantitatively alters the wage gap. Given this evidence, we will also interpret workers' home region as their "birth" region going forward.[12]

To study individuals' wage gains as they move jobs, we define job switches as cases where a worker changes jobs between two establishments without an intermittent unemployment spell.[13] For cross-region switches, we define two types of moves: migration and commuting. In the former, the worker changes his job and residence location, which we observe, while in the latter only the job location is changed. The distinction is useful because we expect that workers that commute to a new job are paid a smaller wage premium than workers that also have to move their residence. Since the residence location is only reported at the end of each year, we define migration as an instance where a worker

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[12]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 residence location when they first enter the labor market shapes their attachment and biases.

[13]Since our data provide the exact start and end date of each spell, time aggregation is not an issue. Note that our data also contain information, such as the benefits received, for the unemployment spells during which workers receive unemployment benefits. However, workers do not appear in the data if they are self-employed, in the public sector, or out of the labor force. We include cases where we observe a time lag between two employment spells as a job-to-job move, since this lag could represent time relocating, etc., and cannot be an actual unemployment spell since then we would observe the worker's status as unemployed in the data. We analyze alternative definitions in robustness exercises below.

Figure 3: Wage Gains from Cross-Region Moves

(a) East to West Move

(b) West to East Move
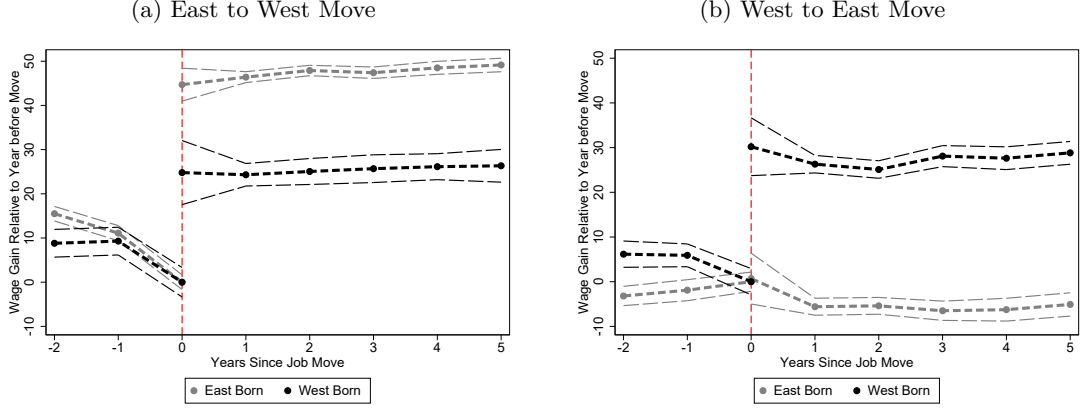
switched jobs between regions and lived in the region of her first job in the year prior to the move and in the region of the second job at the end of the year of the move. The remaining cases are defined as commuting. We analyze alternative definitions below.

Let d_{it}^x be a dummy for a job move of type $x \in \mathbb{X}$, where $\mathbb{X} = \{EW_m, EW_c, WE_m, WE_c, EE, WW\}$ captures moves from East to West via migration and commuting, West to East via migration and commuting, within-East, and within-West, respectively. 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 $\tau \in \{t-3, ..., t+5\}$ around t:[14]

$$\Delta w_{i\tau} = \sum_{x \in \mathbb{X}} \beta_{x,\tau}^{West} d_{it}^x (1 - \mathbb{I}_i^{East}) + \sum_{x \in \mathbb{X}} \beta_{x,\tau}^{East} d_{it}^x \mathbb{I}_i^{East} + B_\tau X_{it} + \rho_i + \epsilon_{it}, \qquad (2)$$

where $\Delta w_{i\tau}$ is the change in an individual's average annual wage between the year τ used in the given regression and the previous year, $\mathbb{I}_i^{East}$ is a dummy for whether an individual's home region is East Germany, X_{it} is a set of time-varying controls, and ρ_i are individual fixed effects.[15] The controls X_{it} include a dummy for the current work region and its interaction with the home region, 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. The coefficients $\beta_{x,\tau}^{West}$ and $\beta_{x,\tau}^{East}$ capture the real wage gains from making a job-to-job transition relative to the wage growth obtained by staying at the same establishment, which is the omitted category. To trace out the wage dynamics over multiple years, we run the regression on an extended period from 2004-2014.

Figure 3a plots the estimated wage gains of a migration move to the West – i.e. the predicted wage from the coefficients $\beta_{EW_m,\tau}^{West}$ and $\beta_{EW_m,\tau}^{East}$, translated into levels, and normalized around the wage

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[14]In practice, we pool together all the data for time periods t from 2004 to 2014, which gives us an unbalanced panel. In general, the unbalanced nature of the panel could be problematic for interpreting pre- and post trends. In our application, we are not too concerned since, as we will show, we do not observe any pre- or post-trends and, in fact, we use only the estimate for the wage growth on impact for our main analysis.

[15]We split the year of the move into two, dependent on whether the time is before or after the move.

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level of the year of the migration. Figure 3b presents the wage gains for West-to-East migration. For comparison, in Figures 4a-4b we plot the estimated wage gains for within-region job-to-job switches from regression (2) against the wage gains from a migration away from home.

The two sets of figures show three results. First, workers that move from East to West see their wage increase steeply: East-born workers receive on average a 45% wage increase relative to their average within-establishment wage growth. Second, wage gains are asymmetric: a worker's real wage gain from leaving her home region is significantly larger than the wage gain from returning. Third, while migration moves are associated with larger gains, workers' wages increase steeply even when changing employer within region.

A tempting conclusion based on the first result would be that sorting is irrelevant to explain the regional wage gap, and that East-born workers face a very a large cost of leaving their home region, which is compensated by the large wage gains. However, this conclusion would be flawed, since the workers that we observe moving between regions are obviously selected: they are the ones that have received job offers sufficiently appealing to make them migrate. In fact, as the third result points out, a move across regions is also a move up the job ladder, and we should benchmark the cross-regional wage changes with these within-region gains to net out the effect of mover selection. Our model will allow us to do so structurally. Finally, the asymmetry of wage gains between leaving the home region and returning shows that workers need to be further compensated to leave their home region, and highlights the importance of distinguishing between different workers' types.

We present the full estimates from specification (2) for $\tau = 0$ in Table 13 in Appendix F and note that the wage gains from commuting are smaller than those for migration but follow a similar ordering, as expected. We then perform several robustness checks, which are run on the core sample period. First, we analyze whether our results are sensitive to our definition of job switches by adding to the benchmark regression a control for the number of months passed between subsequent employment spells, to capture that workers may be non-employed between jobs. Alternatively, we define job switches only as cases where the new job starts within two months of the old one. Columns (1)-(2) of Table 13 in Appendix F show that our findings are robust to these alternatives.[16] Second, we study different definitions of migration. Even though some job switchers do not change their reported residence, they might for example obtain a second home in their new job location. Such job switchers might behave more like migrants than commuters, leading us to overestimate the wage gains of commuters in the baseline. To analyze the sensitivity of our results to this issue, we first define all cross-region job moves that exceed a distance of 150km as migration, regardless of whether the residence location changes. We alternatively examine a cutoff of 100km, and finally we classify all job switches to the region in which the worker is currently not residing as migration, regardless of the distance. Columns (3)-(5) of Table 13 show that the wage gain of commuters falls a bit, as expected, but our overall conclusions remain unchanged.

Table 14 in Appendix F presents benchmark estimates for different sub-groups and shows that the

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[16]We do not include job switches through unemployment because, as our model will show, wages after unemployment spells should only depend on the unemployment benefit.

Figure 4: Wage Gains from Within-Region Moves

(a) East to West Move

(b) West to East Move
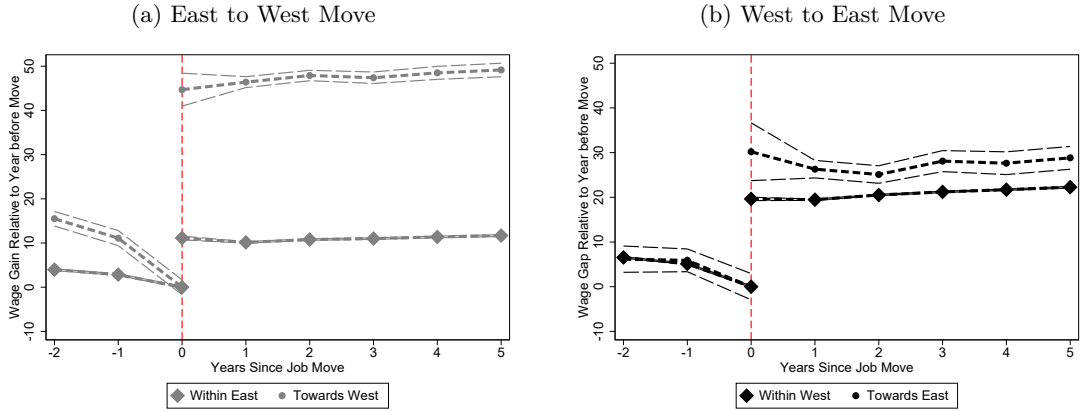
results are consistent, though we do not find home bias for older workers.[17] We also do not find home bias for non-German immigrants, for whom we define the home region in the same way as for German natives as their first region of residence in Germany. This finding makes sense since these workers are presumably less attached to specific regions in Germany.

Fact 3: Frequent Moves across Regions, but Biased Labor Flows

While workers obtain substantial wage gains from moving across regions, it is possible that moving occurs only rarely due to large mobility frictions. We next show that workers are in fact quite mobile across regions, but that their mobility flows are severely biased towards their home region.

Table 2 presents a few cross-regional mobility statistics for our core sample of workers. The first row shows that during our core period 2009-2014, 3% of employment spells by West-born workers and 16% of spells by East-born workers are not in their home region. Overall, of the workers in our sample, 8% of West-born and 30% of East-born have at some point had a job in the other region (row (2)). Thus, there is substantial mobility across the border, especially by East German workers. However, as row (3) indicates, more than half of workers that have been employed in the other region have since returned to a job in their home region, and workers on average spend only 3 years employed in the other region (row 4). The final three rows of Table 2 present some characteristics of workers that never left their home region, have moved to the other region, and that have returned, respectively. While movers are slightly more likely to be college-educated than stayers, less educated workers are also likely to move, comprising about three quarters of all movers from the East.[18] Table 15 in Appendix F shows the statistics split by whether a worker moved in the early or in the late part of the sample period,

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[17]While we would have expected to find home bias for this group as well, a force working against this intuition is that older workers have lower mobility than the young and move for other, often involuntary reasons. Their wage gains are also much smaller.

[18]Note that we observe a higher share of males than in the general population since our sample consists only of full-time workers, which are more likely to be male.

Table 2: Summary Statistics on Mobility

		(1)			(2)		
		Home: West			Home: East		
(1)	Share in foreign region	3.0%			16.1%		
(2)	Crossed border (job / residence)	8.4% / 3.7%			30.0% / 13.3%		
(3)	Returned movers	54.6%			52.6%		
(4)	Mean years away	3.27			2.96		
		Stayers	Movers	Returners	Stayers	Movers	Returners
(5)	Age at move	−	32.7	31.9	−	30.8	30.0
(6)	Share college	.23	.35	.38	.20	.26	.22
(7)	Share male	.70	.65	.70	.57	.64	.69

Notes: Row (1) shows the share of employment spells by workers not in their home region in our core period, 2009-2014. Row (2) shows the share of workers still in the sample in our core period that have ever worked or lived in their non-home region. Row (3) shows the share among those workers that have ever worked in their non-home region that have since returned to a job in their home region, and row (4) shows the mean number of years away. Rows (5)-(7) present the average age, college share, and male share among workers that have never moved out of their home region ("Stayers"), workers that have moved ("Movers"), and workers that have moved and returned ("Returners").

and shows that a substantial fraction of movers has returned home in both samples. As a result of the significant return migration, while the net outflows of East workers to the West were very large in the 1990s, in our core period they are very minor (Figure 20a in Appendix E) and the increase in the total stock of workers away from their home region has gradually leveled off (Figure 20b in Appendix E).

To show formally that workers' mobility is biased towards their home region, we estimate a gravity equation for workers' flows between counties. Gravity equations are frequently used in international trade to explain trade flows (e.g., Eaton and Kortum (2002), Chaney (2008)). Here, we apply these techniques to the flows of workers. We show that geographic barriers along the former East-West border do not play a role in explaining mobility across the two regions, while a worker's type (East or West German) does.

Let $n_{o,d,t}^h$ be the total number of workers with home region h that were in a job in county o in year $t-1$ and are in a new job in county d in year t. These workers may or may not have been unemployed in between jobs.[19] We compute the share of these job-to-job switchers from county o moving to county d (which can be equal to o) across all years in our core period as

$$s_{o,d}^h = \frac{\sum_t n_{o,d,t}^h}{\sum_t \sum_{d \in \mathbb{D}} n_{o,d,t}^h}$$

where $\mathbb{D}$ is the set of all the 402 counties in both East and West Germany.[20] We use these shares to

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[19]We also computed the results excluding all workers with intermittent unemployment. The results are similar, see the last column of Table 17 in Appendix F.

[20]We observe at least one worker flow in some year for $94,203$ out of the $161,000$ possible origin-destination pairs. While we do not use the zeros for our estimation as in most of the literature, note that we observe flows for the majority of pairs.

fit the gravity equation

$$\log s_{o,d}^h = \delta_o^h + \gamma_d^h + \sum_{x \in \mathbb{X}} \phi_x D_{x,o,d} + \xi_{o,d} \sum_{y \in \mathbb{Y}} \psi_y D_{y,o} + \epsilon_{o,d}^h, \tag{3}$$

where δ_o^h and γ_d^h are county of origin and destination fixed effects, respectively, which differ by workers' home region, $D_{x,o,d}$ are dummies for buckets of distance traveled between origin and destination, $D_{y,o}$ are dummies for buckets of the distance between the origin county and the East-West border, and $\xi_{o,d}$ is a dummy that is equal to one if the move between o and d is a move between East and West Germany. The set of buckets $\mathbb{X}$ contains 50km intervals from 50km-99km onward to 350km-399km, and an eighth group for counties that are further than 399 km apart. The set of buckets $\mathbb{Y}$ contains the intervals 1km-99km, 100-149km, 150-199km, and more than 199km.[21]

The regression investigates three channels that could affect worker flows. First, the dummies $D_{x,o,d}$ capture the role of distance. If workers are less likely to move between counties that are further apart, then the coefficients ϕ_x should decline with distance. Second, the term involving the cross-border dummy $\xi_{o,d}$ reflects the role of geographical barriers affecting mobility between East and West Germany. If all workers, regardless of their home region, are less likely to make a job switch if that switch involves moving between East and West Germany, then the coefficients ψ_y should be negative. We refer to this effect as "geographical border effect". We allow cross-region mobility to vary with the distance of the worker's current location from the border to allow for the possibility that workers in origin counties closer to the border find it easier to cross. Finally, the home-region specific fixed effects δ_o^h and γ_d^h capture the fact that some counties may be more attractive than others 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. For example, if γ_d^h is high for a destination then a high share of workers of type h move into that county regardless of their origin location and regardless of whether these workers have to cross the East-West border. To the extent that these fixed effects differ systematically between an East and a West German worker for a given region's counties, the two types of workers have a different valuation for being in that region. We refer to this channel as "identity border effect".

We present the full list of estimated coefficients of regression (3) in Table 16 in Appendix F, and present here only the key coefficients. In Figure 5a, the black line plots the distance coefficients ϕ_x, which we re-normalize into interpretable shares of switchers. As expected, workers are less likely to move to counties that are further away. The gray line plots, for an average county situated at 150-199km from the regional border, the cross-border flows at distances $x \in \mathbb{X}$ for $x \geq 200$ (the coefficients $\phi_x + \psi_{150-199}$), taking the origin and destination effects as constant.[22] The lines are almost on top of each other. Thus, conditional on distance and fixed effects, we do not find a role for the geographical border effect.

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[21]We measure the distance to the border as the distance to the closest county in the other region.

[22]We need to fix border distance since the friction depends on it, for any distance traveled. The results for other fixed border distances are similar.

Figure 5: Geography versus Identity

(a) Geography

(b) Identity: Destination FE
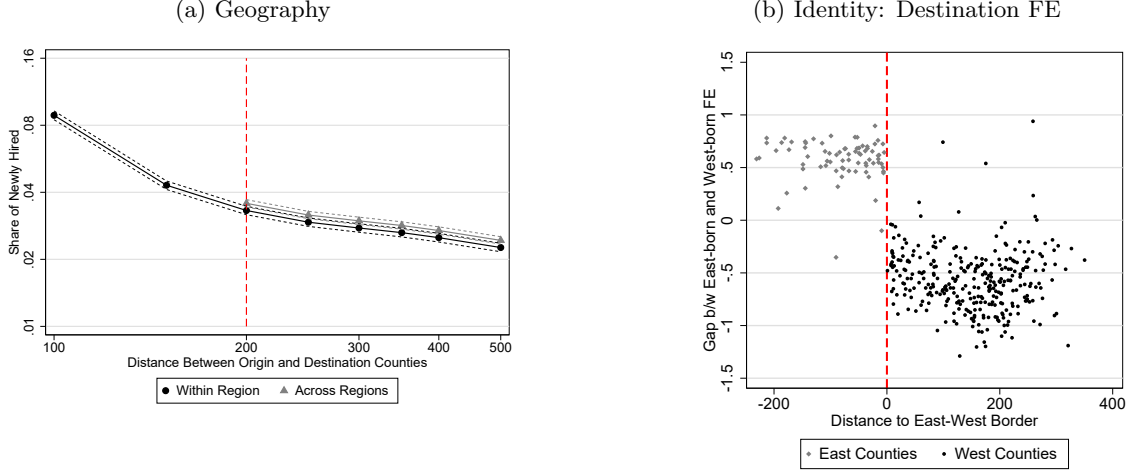
Finally, Figure 5b shows that there is a strong identity border effect. For each county, we compute the difference between the destination fixed effect for East- and West-born workers. We then plot these differences against each county's distance to the East-West border, defined so that East counties have negative distance.[23] The figure shows that East individuals have significantly higher destination fixed effects for the East, indicating that they are more likely to move to counties in the East than West workers regardless of distance. Conversely, East-born workers are less likely to move to counties in the West. Figure 21 in Appendix E presents the origin fixed effects, and highlights that workers are also less likely to move out of counties in their home region. The results imply that both East and West workers have a strong "home bias".

The home bias result holds for various subgroups of the worker population. Since the mobility matrix is more sparse for these subgroups, we replace the distance-specific border effects with simple dummies and let the fixed effects no longer be type-specific. Specifically, we run

$$\log s_{o,d}^h = \delta_o + \gamma_d + \alpha \mathbb{I}^{East} + \sum_{x \in \mathbb{X}} \phi_x D_{x,o,d} + \sum_{k \in \mathbb{K}} \beta_k \mathbb{I}^k + \epsilon_{o,d}^h, \tag{4}$$

where $\mathbb{K} = \{R(o) \neq R(d), R(o) = h, R(d) = h\}$ and $\mathbb{I}^{East}$ is equal to one if a worker's home region is East Germany. The term $\mathbb{I}^{(R(o) \neq R(d))}$ is a dummy for cross-region moves, which captures the geographical border effect. The terms $\mathbb{I}^{(R(o)=h)}$ and $\mathbb{I}^{(R(d)=h)}$ are dummies that equal one when the origin county and the destination county, respectively, are equal to the home region, and capture the identity border effect. If the identity of the worker does not matter, then the coefficients on these latter two dummies should be equal to zero. Table 17 in Appendix F presents the coefficients for different sub-groups of

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[23]As known in gravity equations, the level of the fixed effects is not identified. Therefore, we normalize the fixed effects for both East-born and West-born workers, relative to the average fixed effect, weighted by the number of within-region counties in such a way to assign equal weight to East and West Germany. This normalization is without loss of generality, since we are interested only in the relative fixed effects across counties, and not in their level.

the population and shows that while the attachment to the home region is weaker for skilled workers and for non-Germans, identity is an order of magnitude more important than geography in explaining cross-border mobility for all groups. The results continue to hold if we exclude job-to-job transitions separated by a spell of unemployment.

4 A Multi-Region Model of a Frictional Labor Market

We next develop a model to interpret our empirical findings. The model is useful because the empirical analysis has three shortcomings. First, the magnitudes we find for wage gains across regions are not directly interpretable since the observed movers are selected: they have received a good enough offer from the other region to incentivize them to move. Second, a model is necessary to map the observed differences between East- and West-born workers into relevant primitives. The data, interpreted through our model, allows us to estimate workers' preferences for their home region, skills, and opportunities to move, and to distinguish these from generic migration costs. Finally, the model provides a laboratory to study the macro implications of the various frictions, taking into account firms' endogenous response to changes in the labor supply.

We develop a parsimonious model of frictional labor reallocation, which is designed to leverage the matched employer-employee data that we described in the previous sections. Our model builds on the work of Burdett and Mortensen (1998) and on more recent empirical applications, such as Moser and Engbom (2018). We depart from this previous work along two important dimensions: we consider J distinct regional markets, each inhabited by a continuum of heterogeneous firms; and we consider I different types of workers, which are allowed to be biased towards one or more regions. Workers and firms all interact in one labor market that is subject to both labor market reallocation frictions that prevent workers from moving freely between firms, as in the labor literature (e.g., Burdett and Mortensen (1998)), and spatial frictions that distort the movement of workers between regions, closer to the work in spatial macro and trade (e.g., Caliendo, Dvorkin, and Parro (2019)). Including within-region labor reallocation across firms is necessary since every move between regions is also a move between firms. We thus need to benchmark the wage gains of an across-regions move to those of a within region move across firms. Spatial frictions are generated both by migration costs and by workers' home bias, which we will estimate. We determine regional price differences through a stylized goods market with a fixed factor of production, which will allow us to take into account congestion effects in our counterfactuals in Section 5 below. To our knowledge, we develop the first general equilibrium model that encompasses both spatial and reallocation frictions within a unified framework.

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4.1 Model Setup

We first provide a broad overview of the environment. We then describe the equilibrium in the goods market, which pins down regional price levels. We finally turn to the labor market equilibrium, which is our key focus. We study the problem of workers and firms, and discuss how the labor market clears.

Environment. Let time be continuous. There are $\mathbb{J} = \{1, ..., J\}$ regions in an economy which is inhabited by a continuum of mass 1 of workers of types $i \in \mathbb{I}$, with $\mathbb{I} = \{1, .., I\}$. Throughout the text, we will use superscripts for worker types and subscripts for regions. The mass of workers of type i is $\bar{D}^i$, where $\sum_{i \in \mathbb{I}} \bar{D}^i = 1$. Workers of type i have a preference parameter τ_j^i for being in region j, and consume both a tradeable 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 tradeable good and local good, respectively. Workers also differ in their ability. Specifically, a worker of type i produces θ_j^i units of output per time unit in region j. Hence if this worker is employed at wage rate w per efficiency unit, he earns an income of $w\theta_j^i$. Worker i's indirect utility from receiving wage rate w in region 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 regional price level, P_c is the price of the tradeable good, and $P_{h,j}$ the price level of the local good in region j.[24] We normalize $P_c = 1$.

Workers operate in a frictional labor market. A mass e_j^i of workers of type i in region j is employed and a mass u_j^i is unemployed. An employed worker of type i located in region j faces an arrival rate of job offers from region x of $\varphi_{jx}^i \lambda_x$, where λ_x is the endogenous rate of offers from firms in region x, determined below, and φ_{jx}^i is an offer arrival wedge. This wedge captures for example that offers from firms in a given region may be more likely to reach workers born in that region due to reliance on social networks and referral for offers (as in, e.g., Galenianos (2013)). Unemployed workers face arrival rate $\nu\varphi_{jx}^i\lambda_x$, where ν modulates the relative search intensity of unemployed workers, as in, e.g., Moscarini and Postel-Vinay (2016). Workers moving between j and x also incur a utility cost κ_{jx}^i that captures any monetary and non-monetary one-time cost associated with the move across regions, similar to Caliendo, Dvorkin, and Parro (2019). Workers' job offers are drawn from region-specific endogenous distributions of wage offers $\{F_j\}_{j \in \mathbb{J}}$. Upon receiving an offer, workers decide whether to accept or decline. Workers separate into unemployment at region-type-specific rate δ_j^i, and receive an unemployment benefit rate equal to b_j^i when unemployed.

On the firm side, there is a continuum of firms exogenously assigned to regions $j \in \mathbb{J}$, where M_j is the mass of firms in region j and $\sum_{j \in \mathbb{J}} M_j = 1$. Within each region, firms are distributed over labor productivity p according to density function $\frac{\gamma_j(p)}{M_j}$ with support in a region-specific closed set $[\underline{p}_j, \bar{p}_j] \subseteq \mathbb{R}^+$.[25] Firms post vacancies to hire workers to produce output. We denote by l_j^i the measure of workers of type i employed per vacancy, 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 of the firm. 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

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

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

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 region j of K_j and equilibrium price ρ_j. Each firm p in region j decides how many vacancies $v_j(p)$ to post, subject to a vacancy cost $\xi_j(v)$, what wage rate $w_j(p)$ to offer, and how to allocate labor across the production of the two goods, taking prices in the output market as given. Each vacancy meets workers at a rate that we normalize, without loss of generality, to be equal to one multiplied by the exogenous wedge φ_{jx}^i. All agents discount future income at rate r.

In our model, firms compete for all worker types in one unified labor market. To our knowledge, this is a novel feature of our wage-posting environment. Previous work with heterogeneous types, see for example 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 will determine, endogenously, the composition of worker types it can attract.

Goods Market. We show that, given the within-firm optimal allocation of labor to production and demand for land, the firm's wage posting problem boils down to a linear maximization problem that is similar to the standard setup in the wage posting literature (e.g., Mortensen (2005)).

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

$$\hat{\pi}_j(w) = \max_{n_h, n_c, k} p n_c + P_{h,j} (p n_h)^{1-\alpha} k^\alpha - \rho_j k \tag{5}$$

subject to $n_c + n_h = n_j(w)$. As we show in more detail in Appendix C.1, standard optimization and market clearing conditions imply that in equilibrium the relative price between any two regions j and x satisfies

$$\frac{P_j}{P_x} = \left(\frac{P_j Y_j}{P_x Y_x} \right)^{\alpha(1-\eta)} \left(\frac{K_j}{K_x} \right)^{-\alpha(1-\eta)}, \tag{6}$$

where $P_j Y_j$ is the nominal output of region j. This condition illustrates that if more labor moves to region j, thus increasing output Y_j relative to Y_x, then the relative local price index P_j/P_x rises. Intuitively, the presence of more workers raises demand for the local good, which pushes up the equilibrium price of the fixed factor. Equation (6) also highlights that in order to calculate the change in relative prices as a function of the change in relative GDP, we only need to know the overall share of land payments in GDP, which is given, due to the chosen functional forms, by $\alpha(1-\eta) = \frac{\rho_j K_j}{P_j Y_j}$.

Plugging the labor demand of the firm $n_h = \frac{\rho_j}{p} \frac{1-\alpha}{\alpha} k$ and the equilibrium price for land ρ_j from Appendix C.1 into (5), we can simplify $\hat{\pi}(w)$ to

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

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 next solve for the equilibrium in the labor market, given the regional price index P_j.

Workers. Workers randomly receive offers from firms, and accept an offer if it provides higher expected value than the current one. As is known, this class of models yields a recursive representation. We next derive the expected value of a job offer and the value functions for employed and unemployed workers, respectively.

Employed workers of type i in region j earning wage w randomly receive offers from region x with associated wage w'. Given an offer, workers maximize utility by solving

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

where $W_j^i(w)$ is the value of employment at wage w in region j, $W_x^i(w')$ is the value of employment in region x at wage w', and $\kappa_{jx}^i = 0$ if $j = x$. The terms ϵ_d and ϵ_a are idiosyncratic shocks drawn from a type-I extreme value distribution with zero mean and variance σ, as in, for example, Caliendo, Dvorkin, and Parro (2019), which capture shocks to workers' preferences for being in a specific region. As in this earlier work, these shocks are useful to simplify the model characterization and computation. Given the properties of the type-I extreme value distribution, the probability that an employed worker accepts an offer is given by

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

and the expected value of an offer is

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

Similarly, unemployed workers of type i in region j obtain random offers and compare them to the value of unemployment U_j^i by solving

$$\max \left\{ U_j^i + \varepsilon_u; W_x^i(w') - \kappa_{jx}^i + \varepsilon_e \right\},$$

where ϵ_u is also type-I extreme value. The probability of an unemployed worker accepting an offer is $\mu_{jx}^i\left(b_j^i, w'\right)$, which is defined analogously to before using the value of unemployment, and the expected value of an offer equals

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

Given these offer values, the discounted expected lifetime value of employment $W_j^i(w)$ of a worker i earning wage w in region j solves

$$rW_j^i(w) = \frac{w\theta_j^i\tau_j^i}{P_j} + \sum_{x\in\mathbb{J}} \varphi_{jx}^i\lambda_x \left[\int V_{jx}^i(w,w')\, dF_x(w') - W_j^i(w)\right] \tag{7}$$
$$+ \delta_j^i \left[U_j^i - W_j^i(w)\right],$$

which sums over the worker's flow benefit from employment, in real terms, the expected value from finding a new job, and the continuation value in case of termination.

The expected value of unemployment U_j^i is similarly

$$rU_j^i = \frac{b_j^i\theta_j^i\tau_j^i}{P_j} + \nu\sum_{x\in\mathbb{J}} \varphi_{jx}^i\lambda_x \left[\int V_{jx}^i\left(b_j^i,w'\right) dF_x(w') - U_j^i\right]. \tag{8}$$

Firms. Since the firms' production functions are linear, the firm-level problem of posting vacancies and choosing wages can be solved separately. Following the literature (e.g., Burdett and Mortensen (1998)) and motivated by our empirical results which have shown that in the last few years the wage gap has been mostly constant and the net flows between regions minor, we focus on steady state. Employers choose the wage rate that maximizes their steady state profits for each vacancy, which are

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

where we have used that the net revenues from the goods market at a given wage are $\hat{\pi}_j(w) = p\sum_{i\in\mathbb{I}} \theta_j^i l_j^i(w)$. A higher wage rate allows firms to hire and retain more workers. On the other hand, by offering a higher wage, firms cut down their profit margin, $p-w$. The complementarity between firm size and productivity implies that more productive firms offer a higher wage, just as in the standard Burdett-Mortensen setup. However, unique to our framework, firms need to take into account that their wage posting decision also impacts the types of workers they attract and their region of origin.

Once wages have been determined, firms choose the number of vacancies to post by solving

$$\varrho_j(p) = \max_v \pi_j(p)\,v - \xi_j(v),$$

where $\pi_j(p)$ are the maximized profits per vacancy from (9). The size of a firm p in region j is given by $l_j(w_j(p))v_j(p)$, where $w_j(p)$ is the profit-maximizing wage.

The vacancy posting policy from the firm problem gives us the endogenous arrival rate of offers from each region

$$\lambda_j = \int_{\underline{p}_j}^{\bar{p}_j} v_j(p)\gamma_j(p)\, dp, \tag{10}$$

and the wage policy gives us the endogenous distribution of offers

$$F_j(w) = \frac{1}{\lambda_j} \int\limits_{\underline{p}_j}^{\hat{p}_j(w)} v_j(p)\,\gamma_j(p)\,dp, \tag{11}$$

where $\hat{p}_j(w) \equiv w_j^{-1}(w)$ is the inverse of the wage function, giving productivity p in region j associated with wage w. This inverse exists since the wage function within a given region is strictly increasing as in the standard framework. Allowing the firm size to be affected by both wage and vacancy costs introduces an additional free parameter, which will allow us to match the data by decoupling the relationship between wage and size.

Labor Market Clearing. To close the model, we need to describe how the distribution of workers to firms is determined. We first determine the steady state mass of workers per vacancy $l_j^i(w)$. We then solve for the mass of unemployed and employed workers.

Define by $N_j^i = e_j^i + \nu u_j^i$ the effective number of workers of type i in region j, and define by $\varphi_j^i \equiv \sum_{x\in\mathbb{J}} \varphi_{xj}^i (N_x^i / \sum_{x\in\mathbb{J}} N_x^i)$ a weighted average of the offer wedges across all regions from which a firm could hire a worker. Note that employed and unemployed workers are weighted differently due to their different search intensities. We can obtain the steady state value of $l_j^i(w)$ from its law of motion

$$\dot{l}_j^i(w) = \mathcal{P}_j^i(w)\,\varphi_j^i \bar{D}^i - q_j^i(w)\,l_j^i(w),$$

where $\mathcal{P}_j^i(w)\,\varphi_j^i \bar{D}^i$ is the hiring rate at which a vacancy in region j gets filled by workers of type i from any region, and $q_j^i(w)$ is the separation rate. The hiring rate is given by the product of three terms: i) the exogenous total mass of workers, $\bar{D}^i$, which determines the likelihood that workers of type i are randomly reached by an offer; ii) the average wedge φ_j^i, which modulates the probability that workers of type i are reached by vacancies posted in region j; iii) the probability $\mathcal{P}_j^i(w) \in [0,1]$ that an offer w posted in region j is accepted by workers of type i. The acceptance probability is

$$\mathcal{P}_j^i(w) \equiv \sum_{x\in\mathbb{J}} \frac{\varphi_{xj}^i N_x^i}{\sum_{x'\in\mathbb{J}} \varphi_{x'j}^i N_{x'}^i} \left[\frac{1}{N_x^i} \left[\int \mu_{xj}(w',w)\,dE_x^i(w') + \mu_{xj}^i(b,w)\,\nu u_j^i \right] \right], \tag{12}$$

where $E_j^i(w)$ is the mass of employed workers of type i at firms in region j receiving at most w, with $E_j^i(w(\bar{p}_j)) = e_j^i$. This acceptance probability is a weighted average of the probabilities that a random employed or unemployed worker of type i accepts a wage offer w, where the weights are given by the probability that a contacted worker is in region x.

The separation rate is

$$q_j^i(w) \equiv \delta_j^i + \sum_{x\in\mathbb{J}} \varphi_{jx}^i \lambda_x \int \mu_{jx}^i(w,w')\,dF_x(w'), \tag{13}$$

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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 regions. In steady state, the mass of workers per vacancy is

$$l_j^i(w) = \frac{\mathcal{P}_j^i(w) \, \varphi_j^i \bar{D}^i}{q_j^i(w)}.$$

(14)

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

$$E_j^i(w) \;\; = \;\; \int\limits_{\underline{p}_j}^{\hat{p}_j(w)} l_j^i(w_j(z)) \, v_j(z) \, \gamma_j(z) \, dz,$$

(15)

where $l_j^i(w)$ is given by (14). The mass of unemployed workers is defined via the flow equation

$$\dot{u}_j^i \;\; = \;\; \delta_j^i e_j^i - \vartheta_j^i u_j^i,$$

where ϑ_j^i is the rate at which workers leave unemployment, given by

$$\vartheta_j^i = \nu \sum_{x \in \mathbb{J}} \varphi_{jx}^i \lambda_x \left[\int \mu_{jx}^i(b, w') \, dF_x(w') \right].$$

In steady state, the mass of unemployed workers is then

$$u_j^i \equiv \frac{\delta_j^i}{\vartheta_j^i + \delta_j^i} \bar{D}_j^i.$$

(16)

To conclude the model setup and summarize the discussion, we define the competitive equilibrium in the labor market.

Definition 1: Stationary Labor Market Equilibrium. *A stationary equilibrium in the labor market consists of a set of wage and vacancy posting policies* $\{w_j(p), v_j(p)\}_{j \in \mathbb{J}}$, *profits per vacancy* $\{\pi_j(p)\}_{j \in \mathbb{J}}$, *firm profits* $\{\varrho(p)\}_{j \in \mathbb{J}}$, *arrival rates of offers* $\{\lambda_j\}_{j \in \mathbb{J}}$, *wage offer distributions* $\{F_j(w)\}_{j \in \mathbb{J}}$, *firm sizes for each worker type* $\left\{l_j^i(w)\right\}_{j \in \mathbb{J}, i \in \mathbb{I}}$, *separation rates* $\left\{q_j^i(w)\right\}_{j \in \mathbb{J}, i \in \mathbb{I}}$, *acceptance probabilities* $\left\{\mu_{jx}^i(w, w')\right\}_{j \in \mathbb{J}, x \in \mathbb{J}, i \in \mathbb{I}}$, *and worker distributions* $\left\{u_j^i, E_j^i(w)\right\}_{j \in \mathbb{J}, i \in \mathbb{I}}$ *such that*

1. *unemployed and employed workers accept offers that provide higher present discounted value, taking as given the wage offer distributions,* $\{F_j(w)\}_{j \in \mathbb{J}}$;

2. *firms set wages to maximize per vacancy profits, and 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 vacancy posting and wage policies, according to equations (10) and (11);*

4. *firm sizes and worker distributions satisfy the stationary equations (14), (15), and (16).*

4.2 Characterization of the Equilibrium

We next proceed to characterize the equilibrium. As mentioned, our model extends the class of job posting models à la Burdett and Mortensen to a setting with J regions and I types of workers that interact in one labor market subject to region-worker specific frictions, preferences, comparative advantages, and mobility costs.

Proposition 1. *The solution of the stationary equilibrium is a set of J region-specific optimal wage functions $\{w_j(p)\}_{j \in \mathbb{J}}$ and $J \times I$ region-type specific separation functions $\left\{s_j^i(p)\right\}_{i \in \mathbb{I}, j \in \mathbb{J}}$ given by*

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

$$
s_j^i(p) = s_j^i(\bar{p}_j) + \int_{p}^{\bar{p}_j} \frac{\partial s_j^i(z)}{\partial z} \gamma_j(z)\, dz,
$$

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

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

and $J \times I$ boundary conditions for $s_j^i(\bar{p}_j)$,

$$
s_j^i(\bar{p}_j) \equiv \delta_j^i + \sum_{x \in \mathbb{J}} \varphi_{jx}^i \lambda_x \int \mu_{jx}^i \left(w_j(\bar{p}_j), w'\right) dF_x(w')
$$

where $s_j^i(p) \equiv q_j^i(w(p))$,

$$
\frac{\partial w_j(p)}{\partial p} = \frac{(p - w_j(p))\left(\sum_{i \in \mathbb{I}} 2\frac{\theta_j^i \varphi_j^i \delta_j^i \bar{D}^i}{s_j^i(p)^3} \frac{\partial s_j^i(p)}{\partial p}\right)}{\left(\sum_{i \in \mathbb{I}} \theta_j^i \frac{\varphi_j^i \delta_j^i \bar{D}^i}{s_j^i(p)^2}\right)},
$$

and

$$
\frac{\partial s_j^i(p)}{\partial p} = \sum_{x \in \mathbb{J}} \varphi_{jx}^i \int \frac{\partial \mu_{jx}^i(w_j(p), w_x(z))}{\partial w} \frac{\partial w_j(p)}{\partial p} v_x(z)\, \gamma_x(z)\, dz.
$$

Furthermore, $v(p) = (c_j')^{-1}(\pi_j(p))$.

Proof. See Appendix C.2. □

In order to understand the structure of our model, it is useful to compare it to the benchmark Burdett-Mortensen model, which is a special case of our model when worker heterogeneity and mobility frictions across regions are shut down, and search intensity from unemployment is equal to 1.[26] In this benchmark case – as is well known – the equilibrium wage policy is as follows: the lowest productivity firm sets the minimum wage that allows it to hire workers from unemployment – i.e. $w\left(\underline{p}\right) = b$ – and the wage policy is an increasing and continuous function of productivity. As a result, workers separate either exogenously or upon receiving a job offer from any firm with a higher productivity, giving a separation rate of $s(p) = \delta + \lambda[1 - F(w(p))]$. The wage policy must be continuous, since a discrete jump in wage cannot lead to a discrete jump in firm size, the reason being that firm size is purely determined by the ranking of wage offers and not by their level. Equilibrium wage dispersion is given by the fact that firms that pay a higher wage are able to attract and retain more workers, and thus firm size is an increasing function of wage paid.

In our setting these insights generalize, but need to be refined. First, since workers receive wage offers from firms in any region, their decision to quit to another firm no longer depends only on the wage offered but instead on the overall value of the job. As a result, the probability that an offer wage w is accepted is no longer $F(w)$, but rather becomes $\mathcal{P}_j^i(w)$, which incorporates that wage offers will have different acceptance probabilities from different types i and depending on the region j where they are posted. Second, firms take into account that by changing the posted wage rate they can affect the composition of workers they attract. While within a given type i-region j pair firm size depends only on the ranking of firms' wage offers, as in the benchmark model, across regions and worker types also the level of the wage is relevant. While in principle this feature of the model can lead to discontinuities in the wage policy, for example if a small wage increase is sufficient to attract workers of an additional type, in practice the presence of the utility shocks ε_a, ε_e, and ε_u preserves the continuity of the wage function. Third, the boundary conditions for the wage of the lowest productivity firms in each region needs to be solved numerically. In our setting, due to the presence of the stochastic shocks, even the lowest productivity firms might be willing to offer a higher wage than the value of unemployed workers within their region.

Our model does not admit an analytical solution. Nonetheless, the previous proposition facilitates the solution of the model and speeds up dramatically its computation. Given the workers' value functions and the optimal wage of the lowest productivity firms, which we have to solve for numerically, the solution of the problem consists simply of solving a system of J plus $J \times I$ ODEs. Specifically, we follow an iterative procedure. Given an initial guess of the wage function, we compute workers' value functions, which in turn allow us to calculate analytically the probability of a move between any two firms, $\mu_{jx}^i(w, w')$, exploiting the properties of the extreme value distributions. Equipped with $\mu_{jx}^i(w, w')$, we have analytical expressions for probability of acceptance and the separation rate, which allows us to determine, in steady state, the number of workers per vacancy $l_j^i(w)$ at any wage. We then use $l_j^i(w)$ to find numerically the boundary conditions for wages $w_j(\underline{p}_j)$. Finally, we update the wage

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[26]Specifically, when $\theta_j^i = \tau_j^i = \varphi_{jx}^i = 1$ for all i, j, and x; $\delta_j^i = \delta$ and $b_j^i = b$ for all i and j; $v = 1$; $\sigma \to 0$; and $\kappa_{jx}^i = 0$.

function by integrating the differential equation shown in the proposition. In practice, this approach allows us to solve the model in just a few seconds.

Sources of Frictions. The model encompasses three types of frictions that prevent the allocation of workers to the most productive firms. As will become evident in Section 5, our model includes as many types of reallocation frictions as we can separately identify using matched employer-employee data.

First, *reallocation frictions*, as in the class of models along the lines of Burdett and Mortensen (1998), prevent the reallocation of workers to more productive firms even within a region. The friction arises because firms have to pay the convex vacancy posting cost $c_j(v)$ to hire a worker, which implies that the rate at which workers receive job offers, λ_j, is finite. Workers therefore have to wait to receive a better job offer or to exit unemployment.[27]

Second, *migration costs* hinder the mobility of labor between regions. As in spatial models with frictional labor mobility (e.g., Bryan and Morten (2019), Caliendo, Dvorkin, and Parro (2019)), workers have to pay a cost equal to κ_{jx}^i to move across regions. This cost may prevent workers from accepting better job offers if they involve a cross-region move.

Finally, *home bias* hinders the mobility of workers out of their home region. We model three possible sources of home bias: i) workers might be endowed with skills that are more valued in their home region (governed by θ_j^i), ii) workers might prefer to work in their home region (determined by τ_j^i), and iii) workers might have more job opportunities in their home region (governed by φ_{jx}^i). We will refer to these three mechanisms as i) skill bias, ii) taste bias, and iii) offer bias.

Our model encompasses all three sources of frictions in a unified framework. We will refer to migration costs and home bias jointly as *spatial frictions*, since they affect workers' allocation across space. Taking into account both reallocation and spatial frictions is important to obtain correct estimates of each from workers' wages and mobility patterns. For example, the wage gains when workers move across regions, which will be used to estimate the spatial frictions, depend on the distribution of job offers, which in turn depend on the reallocation frictions in the economy. Additionally, the model shows that a wage gap between regions can persist even in the absence of any spatial frictions: if there is a productivity gap between regions and reallocation frictions make it hard for workers to move between firms, then few workers move from low to high wage firms in general. Since more high paying firms are in one region than the other, a spatial wage gap emerges.

We describe and implement in the next section a strategy to separate the three frictions.

5 Quantitative Analysis

We now use the model to study the German labor market. First, we briefly discuss our overall

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[27]In the previous literature, the ratio $\frac{\delta}{\lambda}$, which governs this friction, has become known as the "market friction parameter" (e.g., Mortensen (2005)).

estimation strategy. Then, we provide a heuristic structural identification argument to show how the structure of the model, together with appropriate empirical moments, allows us to separately identify the different sources of frictions. Next, we estimate the model. Finally, we discuss the model fit and the estimated primitive parameters, and use the model to compare the aggregate effects of different policies, either aimed at fostering regional integration or general reallocation of labor to more productive firms. We conclude this section by providing an external validation exercise of the model.

5.1 Overall Estimation Strategy

The general model presented in Section 4 has, in principle, a very large number of primitive inputs. In order to bring the model to our data, we will choose parsimonious functional forms, calibrate outside of the model all the parameters that have a direct empirical counterpart, and estimate the remaining parameters within the structure of the model through simulated method of moments. We also make a few parametric restrictions that, as we explain below, are useful to identify the key primitives of interest.

As emphasized before, Proposition 1 speeds up dramatically the computation of the model. For this reason, we are able to solve the model for millions of different parameter vectors.[28]

Units and Functional Form Assumptions. We consider two regions, East and West Germany, and two worker types, East and West Germans. We set a unit interval of time to be one month.[29] Firms' log productivity is drawn from a Gamma distribution with scale and shape parameters γ_1 and γ_2. We assume that the scale and shape parameters are the same in both regions, and that there is a relative productivity parameter $Z > 0$ which shifts the CDF of the West – i.e. for all $\log p$, $\Gamma_W (\log p + Z) = \Gamma_E (\log p)$. Figure 22 in Appendix E motivates this assumption by showing that the wage distribution in the West has the same shape as in the East, but is shifted to the right, while the firm size distribution is similar in both regions.

We parametrize the vacancy cost function as $c_j(v) = \frac{\chi_{0,j}^{-\chi_1}}{1+\chi_1} v^{1+\chi_1}$, where $\chi_{0,j}$ and χ_1 are parameters to be estimated. This parametrization implies that the equilibrium mass of vacancies posted by a firm with productivity p is $v_j(p) = \chi_{0,j} \pi_j(v)^{1/\chi_1}$. We assume that the curvature χ_1 is constant across regions but allow $\chi_{0,j}$ to be region-specific.

We interpret the migration cost as an opportunity cost of foregone wages (Sjaastad (1962)). Specifically, we assume that the migration cost of a given worker type is symmetric and proportional to the average value of that type, $\kappa_{jx}^i = \kappa \bar{W}^i$, where $\bar{W}^i = \frac{1}{\bar{D}^i - u^i} \sum_{j \in \mathbb{J}} \int W_j^i(w) dE_j^i(w)$. Otherwise, if κ_{jx}^i were a constant for all i, then the migration cost would be more binding for East-born workers since these have on average lower wages at any firm, as we show below. We find this feature undesirable.

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[28] In Appendix D.1, we provide details of the estimation procedure.

[29] 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 Possion rate δ at which unemployment shocks arrive such that $Prob_u = 1 - e^{-\delta}$.

5.2 Inference Through the Lens of the Model

We now show how, using the structure of the model and our rich dataset, we can separately identify the different sources of frictions. As usual, the structural identification rests on the assumptions of the model, as we thoroughly explain in this section.

We first discuss identification of the skill bias, for which we have an exact identification argument. We then turn to the mobility costs, the taste bias, and the offer bias, for which we need to rely on heuristic arguments, which are verified ex-post using Monte Carlo simulations.

Skill Bias. The model yields the following wage equation for an individual born in region i working at firm p in region j

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

The wage of an individual is therefore log additive in an individual fixed effect and a firm fixed effect, as in the empirical specification proposed by Abowd, Kramarz, and Margolis (1999). There is, however, one key difference relative to the benchmark AKM framework: the individual fixed effect is region-specific, thus accommodating the possibility that workers may be better compensated at a firm in their home region than at a comparable firm in the other region, i.e., workers may have a comparative advantage at home. As we explain in more detail in Appendix B.3, we can account for this effect by including an additional dummy for workers not in their home region. We can then recover separately the average fixed effect of East- and West-born workers and a comparative advantage term, subject to normalization. Our model thus yields the specification

$$\log w_{it} = \alpha_i + \psi_{J(i,t)} + \beta \mathbb{I}^{(R(h_i) \neq R(J(i,t)))} + \epsilon_{it}, \tag{17}$$

where, with slight abuse of notation, i indexes here an individual worker rather than a worker type, w_{it} is the wage of worker i at time t, α_i is the worker fixed effect, $\psi_{J(i,t)}$ is the fixed effect for the firm at which worker i is working at time t, and $\mathbb{I}^{(R(h_i) \neq R(J(i,t)))}$ is a dummy that is equal to one if worker i with home region $R(h_i)$ is currently employed at a firm in a different region.

Running specification (17) using data generated from our model, we would recover the absolute advantage of an individual in his home region from

$$\mathrm{E}\left(\hat{\alpha}_E\right) - \mathrm{E}\left(\hat{\alpha}_W\right) = \log \theta_E^E - \log \theta_W^W$$

and the relative comparative advantage from

$$\hat{\beta} = \log \frac{\theta_W^E}{\theta_E^E} + \log \frac{\theta_E^W}{\theta_W^W}.$$

To recover the four θ_j^i we need two normalizations: first, without loss of generality we pick $\theta_E^E = 1$. Second, we can only recover relative comparative advantage, since we cannot distinguish empirically

between East-born workers having a relative disadvantage in the West and West-born workers having a disadvantage in the East (see Appendix B.3). We therefore impose the skill bias to be symmetric, that is we assume that $\frac{\theta_W^E}{\theta_E^E} = \frac{\theta_E^W}{\theta_W^W} \equiv \theta_h$.

Taste Bias and Migration Frictions. We discuss the taste bias and the migration costs together since they are both pinned down by the wage gains of movers. In the model, the average wage gain for an individual born in region i that makes a job-to-job move from region j to region x is given by

$$\Delta w_{jx}^i = \underbrace{\log \frac{\theta_x^i}{\theta_j^i}}_{\text{Skill Bias}} + \int \left(\int \underbrace{(\log w' - \log w)}_{\text{Wage Gain}} \underbrace{\mu_{jx}^i(w, w')}_{\text{Prob. Accept}} \underbrace{dF_x(w')}_{\text{Offers' CDF}} \right) \underbrace{dG_j^i(w)}_{\text{Wages' CDF}}. \tag{18}$$

The first term captures the change in efficiency units of labor provided and depends on whether the worker has a skill bias towards the origin or destination region. The second term captures the change in the wage per efficiency unit paid by the firm, and it is integrated over all the possible moves (w, w'), weighted by the relevant probability of acceptance $\mu_{jx}^i(w, w')$. This component has a double integral because we need to consider all possible origin wages, according to the equilibrium distribution of labor over wages in the origin region G_j^i, and all possible destination wages, according to the wage offer distribution in the destination region F_x.

Both the taste wedge τ_j^i and the mobility cost κ affect the wage gain through their impact on the probability of acceptance $\mu_{jx}^i(w, w')$.[30] To build intuition, consider the limit case when $\sigma \to 0$ – i.e. there are no preference shocks. Then, $\mu_{jx}^i(w, w') = 1$ if and only if

$$W_x^i(w') \quad -\kappa \bar{W}^i \geq \quad W_j^i(w). \tag{19}$$

Since $W_j^i(w)$ is an increasing function of w, equation (19) implies that, all else equal, when the moving cost κ is larger workers have to receive a better wage offer to move across regions. Similarly, since from equation (7) $W_j^i(w)$ is also increasing in τ_j^i, workers that have a lower preference for a given region need to receive better job offers from that region to compensate them for this disutility.

The reasoning shows that the wage gains convey useful information on both the moving cost and the taste bias. Since with our data it is not possible to distinguish between a lower amenity value in the West on the one hand and a higher moving cost from East to West than from West to East on the other, we rely on our identifying assumption that $\kappa_{jx}^i = \kappa \bar{W}^i$ to identify the two parameters separately.[31] Furthermore, without loss of generality, we normalize $\tau_E^E = 1$. Last, consistent with the assumption we made on skill bias, we restrict the taste bias to be identical for East- and West-born workers, i.e., both East- and West-born workers have the same disutility of living away from home. We

---

[30]The flow utility of an individual i employed at a firm that pays wage w per efficiency unit in region 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.

[31]We argue that if we interpret the cost κ as a literal moving cost, then it is reasonable to assume that it is symmetric. We will then charge all region and birth-place specific differences to the taste parameters τ.

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therefore need to pin down two taste bias parameters: the taste bias for being in the home region τ_h, and the relative taste for working in the West τ_W, which simply captures the overall amenity differences across regions.[32] This restriction reduces the dimensionality of the parameter vector to be estimated, thus tightening up the identification and focusing on the key objects of interest.

Equation (18) shows that the wage gains depend additionally on the endogenous wage offer and labor distributions, F_x and G_j^i. We need the structural model to control for these endogenous objects to correctly estimate the κ, τ_h, and τ_W. Nonetheless, we can provide some intuition for the size of these parameters by comparing the relative wage gains across different types of moves.

Consider an East-born worker moving from East to West Germany. Figure (3a) shows that such moves entail on average a very large wage increase. This could be due to three possibilities: i) East German workers dislike working in the West; ii) there is a large migration cost between East and West Germany, thus leading East-born workers to accept only the very best offers; or iii) offers received from the West are on average much higher than the equilibrium wages in the East. Comparing the wage gains of an East German worker moving from East to West to the wage gains of moving from West to East allows us to argue that migration costs cannot be the only explanation. Under our identifying assumption, movers towards the East also face a migration cost, yet their wage does not increase upon a move, as shown in Figure (3b). Similarly, comparing the wage gains of East- and West-born workers for the same move from East to West Germany allows us to argue that differences in the offer distribution cannot be the only explanation: by assumption, East- and West-born workers draw from the same distribution of offers, yet West-born workers have a much smaller relative wage increase when moving towards the West. This argument demonstrates that individuals must have a taste bias towards their home region since otherwise we should not observe the steep asymmetry between East- and West-born workers.

Offer Bias. In the model, the rate at which workers of type i currently employed in region j separate towards a job in region x is given by

$$
\mu_{jx}^i \;=\; \underbrace{\varphi_{jx}^i \lambda_x}_{\text{Arrival Rate}} \;\times\; \underbrace{\int \left(\int \underbrace{\mu_{jx}^i \left(w, w'\right)}_{\text{Prob. Accept}} \; \underbrace{\mathrm{d}F_x \left(w'\right)}_{\text{Offers' CDF}} \right) \underbrace{\mathrm{d}G_j^i \left(w\right)}_{\text{Wages' CDF}}}_{\text{Average Probability of Accepting}} . \tag{20}
$$

The separation rate is therefore the product of i) the rate at which offers from region x arrive to workers i and ii) the probability, on average, that an offer is accepted. As just discussed, the second term is pinned down by moments reflecting workers' wage gains. The first term depends on the exogenous wedges of interest, φ_{jx}^i, and the endogenous overall arrival rate of offers from region x, λ_x, which is a function of the endogenous number of vacancies posted.

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[32]Given the restrictions, the parameters are: $\tau_E^E = 1$, $\tau_W^E = \tau_h \tau_W$, $\tau_W^W = \tau_W$, $\tau_E^W = \tau_h$.

Since, by assumption, West- and East-born workers draw offers from the same distribution, we can recover the size of the wedges from the rates of job-to-job mobility across regions and by worker types. For example, consider the mobility rates of workers currently in East Germany towards the West. As we show below, West-born workers in the East move towards jobs in the West at roughly three times the rate of East-born workers. Since West- and East-born workers face the same λ_W, the difference could arise either because West-born workers receive more offers from the West ($\varphi_{EW}^W > \varphi_{EW}^E$) or because West-born workers are more likely to accept offers from the West, possibly because they have a taste or skill bias towards it. Since the taste and skill bias are already pinned down by wages, targeting the observed flows allows the model to recover the offer bias.

Following the skill and taste biases, we restrict also the offer bias to be symmetric: we assume that $\varphi_{EW}^E = \varphi_{WE}^W \equiv \varphi_{hf}$, which is the wedge for offers from the home region to the foreign region. Similarly, $\varphi_{WE}^E = \varphi_{EW}^W \equiv \varphi_{fh}$, which captures the wedge from the foreign region back home. We also assume that within region there are no offer biases, and normalize these wedges, without loss of generality, to one: $\varphi_{jj}^i = 1$ for all i and j.

5.3 Estimation

We now estimate the model in practice. We first calibrate several parameters outside of the model. Next, we estimate the skill bias separately using the AKM. Finally, we jointly estimate the remaining parameters. We describe how we compute the moments needed for the estimation in the data and how they relate to the structural parameters of the model.

To compute the empirical moments, we use both the LIAB and the BHP data, drawing on their respective advantages. The matched employer-employee data from the LIAB allow us to compute the job-to-job flows and wage gains at the individual level, which are crucial to identify the components of the home bias and the migration friction. The establishment-level BHP data, on the other hand, contain a significantly larger, and representative, sample of establishments, which provides us with a better estimate of the firm side of the job market. We summarize the 10 directly calibrated parameters and the 13 jointly estimated ones in Table 3.

Calibrated Parameters. We calibrate eight parameters outside of the model, rows (1)-(8) of Table 3.

The share of workers born in the East, $\bar{D}^E$, can easily be computed from the LIAB. Similarly, the share of firms in East Germany, M_E, can be obtained from the BHP. We normalize the mass of firms in East and West Germany to be the same in our estimation, for the following reason. If we calibrated the number of firms to match the empirical mass of 18% of establishments in the East, then workers in the East would have a higher chance of being contacted by a vacancy that requires the payment of a mobility cost than West German workers, since workers have to pay a migration cost when they move across regions but face no mobility cost within regions. We find that outcome undesirable because we see the moving cost as something that captures the actual cost of relocating, which is not specific to

Table 3: Estimated and Calibrated Parameters

		Value
	Parameters Calibrated Outside of the Model	
(1)	$\bar{D}^E$: Share of Workers born in East	32.10%
(2)	M_E: Share of Firms in East	17.90%
(3)	δ^E: Monthly Separation Rate to Unemployment (East-Born)	0.92%
(4)	δ^W: Monthly Separation Rate to Unemployment (West-Born)	0.63%
(5)	b: Unemployment Benefit	$0.60\underline{p}$
(6)	r: Interest Rate (Monthly)	0.5%
(7)	P_E: Price Level in East Germany	0.93
(8)	$\alpha(1-\eta)$: Payments to Fixed Factors as Share of GDP	5.0%
	Estimated Skill Bias	
(9)	θ_h: Comparative Advantage towards Home-Region	0
(10)	θ_W: Absolute Advantage of West-Born	12.78%
	Estimated Remaining Home Bias and Mobility Frictions	
(11)	$1-\tau_h$: Preference for Home-Region	4.92%
(12)	κ: Mobility Cost to Cross-Regions	3.38%
(13)	φ_{fh}: Offer Bias from Home Region	7.21%
(14)	φ_{hf}: Offer Bias from Foreign Region	3.66%
	Estimated Productivity and Amenity Differences	
(15)	Z: Productivity Gain of West-Firms	11.05%
(16)	$1-\tau_W$: Preference for West Germany	-12.56%
(17)	γ_1: Variance of Firm Productivity	0.022
(18)	γ_2: Skewness of Firm Productivity	1.81
	Estimated Labor Market Frictions	
(19)	$\chi_{0,W}$: Level of Vacancy Cost (West)	0.128
(20)	$\chi_{0,E}$: Level of Vacancy Cost (East)	0.098
(21)	χ_1: Curvature of Vacancy Cost	3.66
(22)	σ: Variance of Taste Shocks	0.79
(23)	ν: Relative Search Intensity of Unemployed	1.80

Notes: The table includes the estimation targets and the model generate moments.

East or West Germany. Therefore, we use an equal mass of firms in each region, and then appropriately re-scale all the empirical targets and the share of workers born in the West. For example, we adjust the empirically observed probability of a move from West to East Germany by a factor of $\frac{.5}{.18}$ to be consistent with the model in which 50%, rather than 18% of firms are in the East, and so on.

We assume that the separation rate δ_j^i depends only on workers' type and not on the current region, and we set it equal to the monthly probabilities, computed in the LIAB data, that employed East- and West-born workers separate into unemployment. Our assumption is motivated by the fact that, conditional on a rich set of controls, the average probability of becoming unemployed does not change for a given worker once that worker is in a different region.[33,34] We assume that the unemployment benefit, but not its utility value, is the same irrespective of the worker's birth-region and scaled by the productivity of the last region a worker was employed in: $b_j^i = bZ_j$ for all j and i. In Germany, unemployed workers in both East and West receive about 60% of their previous wage for the duration of their unemployment insurance benefits, and receive welfare benefits afterwards, which are lower (Dustmann (2003), Caliendo, Tatsiramos, and Uhlendorff (2013)). Since empirical search models often set the reservation wage below the level of benefits (e.g., Van Den Berg (1990), Van Den Berg and Ridder (1998)), based on the assumption of a non-pecuniary disutility of being unemployed, we set the unemployment benefit in our baseline calibration to 60% of the productivity level of the lowest productivity firm. We show in Appendix D.2 that setting either higher or lower benefits does not meaningfully alter the estimates of the spatial barriers.

Since individuals in our model are infinitely lived, the interest rate r accounts for both discounting and rates of retirement or death. We pick a monthly interest rate equal to 0.5%. To set the price level in the East P_E, we take the prices estimated for a representative consumption basket including rents from the BBSR (2009) for each county, and compute a population-weighted average across East German and West German counties, respectively. This exercise yields $P_E = 0.93$. Finally, interpreting the fixed factor in the model as land, we set $\alpha(1-\eta)$ equal to 5%, which is the estimate of the aggregate share of land in GDP for the United States, see Valentinyi and Herrendorf (2008). Unfortunately, we are not aware of estimates for Germany. It is worthwhile to notice that $\alpha(1-\eta)$ does not affect the estimation of the model since we feed in the price level P_E directly. It is only relevant for the counterfactuals and policy analysis.

Estimating the Skill Bias. The skill bias can be estimated separately before solving for all other parameters. We implement the AKM regression (17) in the LIAB, following exactly the specification in Card, Heining, and Kline (2013), but using data for both East and West Germany and adding the additional dummy to capture skill bias as described.[35] As is standard, we estimate the model on the

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[33]We compute the probability of becoming unemployed around a migration episode as in the specification (2), and show the results in Figures 23a and 23b in Appendix E.

[34]Of course, unconditionally, the separation rate, as well-known, increases after any job-job migration move.

[35]Following Card, Heining, and Kline (2013), we include time dummies, a polynomial for age interacted with educational attainment, where age is centered around 45 and we omit the linear term. While it is well-known that the variances of firms' and workers' fixed effects are biased due to low mobility, Andrews, Gill, Schank, and Upward (2008) show that

largest connected set of workers in our data, since identification of workers and establishment fixed effects requires firms to be connected through worker flows.[36] This sample includes approximately 97% of West and East workers in the LIAB.

The results show a small *negative* comparative advantage in the home region, indicating that a typical East-born worker is paid, controlling for firm characteristics, almost 1% more if he works in the West.[37] One possible explanation for this finding could be selection, since the workers that move to the West could be those whose skills are particularly valuable there. Since the presence of the premium would require the remaining frictions to be larger to rationalize the lack of East-to-West mobility, we conservatively set the comparative advantage to $\theta_h = 0$.

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

$$\hat{\alpha}_i = \rho_i + \eta \mathbb{I}^i_{East} + \varepsilon_{ij}, \tag{21}$$

where $\hat{\alpha}_i$ is the estimated worker fixed effect, and $\mathbb{I}^i_{East}$ is a dummy for whether the worker's home region is in the East. The difference in the average worker fixed effects $\hat{\eta} = \mathrm{E}\left(\hat{\alpha}_E\right) - \mathrm{E}\left(\hat{\alpha}_W\right)$ pins down θ^W_W. We present these estimated parameters in rows (9) and (10) of Table 3.[38]

Estimating the Remaining Parameters. The remaining 13 parameters need to be estimated jointly via simulated method of moments. Our estimation solves for the set of parameters ϕ satisfying

$$\phi^* = \arg \min_{\phi \in \mathbb{F}} \mathcal{L}\left(\phi\right)$$

where

$$\mathcal{L}\left(\phi\right) \equiv \sum_x \left[\omega_x \left(\frac{m_x\left(\phi\right) - \hat{m}_x}{\hat{m}_x} \right)^2 \right],$$

and where $m_x(\phi)$ is the value of moment x in our model given parameters ϕ, $\hat{m}_x$ is the empirically observed vector of moments, and ω_x is a vector of weights. We now discuss how we compute the 28 empirical targets used in the estimation and how they identify the remaining parameters. We present the moments assigned to five groups in Table 4, where each of the groups receives equal weight in the estimation, and within each group all moments are equally weighted.[39]

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their averages, which we use in this paper, are unbiased. Details are in Appendix B.3.

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

[37]The estimated coefficient is $\beta = 0.019$, of which, based on our assumption, we attribute half to comparative advantage of the East worker in the West.

[38]We can also perform this regression with additional controls for age, gender, and a college dummy. The coefficient on East Germans in that case falls from $-.1278$ to $-.1061$. Hence, most of the difference is due to unobservable heterogeneity.

[39]In Appendix D we present the exact formula for ω_x, which normalizes the squared deviation of each model-implied moment from its empirical counterpart by the average level of the moments within each subgroup. For example, we normalize the squared deviation of each wage gain associated with cross-regional moves by the average wage gain from all the moves. This normalization avoids giving excessive weight to moments with a low $\hat{m}_x$. We then weight the five subgroups of moments equally. In Appendix D we also illustrate the dispersion of our estimated parameter values for the

As discussed, the size of the taste bias and the migration friction are mainly identified from the average wage gains of job-to-job switchers that move across regions. We obtain the empirical wage gains from the wage regression (2) discussed earlier, where we take the coefficients of the year of the job move, shown in column (1) of Table 13 in Appendix F. We present the values of these targeted moments in rows (1)-(4) of Table 4. The size of the offer wedge is identified from the cross-regional flows of workers between jobs. We construct these flows by computing in the LIAB the share of workers that make a job-to-job switch from East to West or from West to East, respectively, in each month, and average each of these moments across all months in 2009-2014. We obtain the moments for both East- and West-born workers (rows (9)-(12) of Table 4). Additionally, we target the share of West-born workers employed in the West and the share of East-born workers in the East from the LIAB to ensure that our steady state equilibrium matches these moments closely (rows 17-18).

To determine the taste bias and the migration cost, our model needs to be consistent with the distributions of wage offers $F_x(w)$ and the joint distributions of firm wage and size $G_j^i(w)$. We rely on moments in the BHP data to match the wage-size distribution $G_j^i(w)$. As discussed, the BHP data are preferable for moments on the firm side, since they are representative at the firm-level. However, since the BHP does not allow us to construct employment by home region, we cannot target distributions that distinguish between East- and West-born workers. We observe the regional wage-size distributions $G_j(w)$ directly in the data, and target three moments from these distributions.[40] First, we seek to match the share of employment at the 10% largest firms within each region and the skewness of the distribution of (log) firm size. These two moments provide information on the overall shape of the wage-size distribution. To construct these moments, we residualize each establishment's log number of workers by removing factors affecting size that are not in our model.[41] We then compute the share of workers in the top decile and the skewness based on the residualized size distribution in each region. These moments are listed in rows 21-24 of Table 4. We additionally target the (log-log) relationship between firm average wage and size (rows 25-26), which we obtain via a regression of establishments' log average wage on log size in each region, where we include the same controls as in the residualization. As we will show in Section 5.7, the relationship between firm size and wage is log linear in the data. Overall, the six moments pin down the skewness and variance of the firm productivity distribution, γ_1 and γ_2, and provide information on the level and the curvature of the vacancy cost function, which are governed by $\chi_{0,j}$ and χ_1.

The distribution of wage offers $F_x(w)$ is not observed in the data. However, as well known, the distribution of wage offers and the equilibrium distribution of workers to firms are directly linked to each other in Burdett-Mortensen setups. The relationship between the offer distribution and the wage-size

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best 5000 parameter draws.

[40]We do not target the wage dispersion in the data, since our model generates only one component of it: the frictional wage dispersion.

[41]We regress the log establishment size on controls for the establishment's share of males, share of old and young workers, the share of workers with specific education levels, industry dummies, time dummies, and an East Germany dummy interacted with time fixed effects, and run this regression separately for each county to allow the regression coefficients to be county-specific. We then obtain the residuals from these regressions.

distribution is modulated by the arrival rate of offers, both on the job and from unemployment, and the separation rates. We therefore target, first, the share of workers flowing between jobs per month within a given region, computed in the same way as the flows across regions (rows 13-16). Second, we target each region's unemployment rate, which we obtain from the Federal Employment Agency (rows 19-20). These moments, together with the ones above, are sufficient to pin down through the model's structure the distribution of wage offers. In terms of model primitives, they help to identify the level and the curvature of the vacancy cost function, and the relative matching parameter from unemployment, ν: given a separation rate δ_j, discussed above , a higher ν implies a lower unemployment rate.

We pin down the productivity shifter Z using two main moments. First, we compute the difference in the average firm component of wages from the AKM, which is calculated analogously to equation (21) with a dummy for whether a firm is in East Germany. Using the firm component has the advantage that it controls for any differences related to worker heterogeneity. Second, we target the gap in real GDP per worker between East and West Germany. We obtain nominal GDP and employment from the national statistical offices of the states, exclude Berlin, and deflate with the price index from the BBSR. These moments are shown in rows (27)-(28).

Finally, we determine the variance of the taste shocks σ. When $\sigma \to 0$, there are no preference shocks and thus, within a given region, workers always climb the job ladder, reallocating from lower to higher wage jobs. Instead, when $\sigma \to \infty$, a workers has always a 50% probability of accepting a job offer, since the preference shocks swamp any other consideration. As a result, the average wage gain upon a move decreases with σ. We can therefore use the size of wage gains from within-region job-to-job moves, which have not been used so far, to discipline how important the taste shocks are (rows 5-8).

Discussion of Model's Assumptions. We conclude this section with a brief discussion of two key assumptions of the model that guide identification: random search and wage posting. These two assumptions are present in the original Burdett and Mortensen (1998) formulation, and thus this section can be interpreted as a justification and discussion of our core modeling choice.

First, our model has random search. 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 parameter φ_j^i. For example, while we estimate φ_W^E as a wedge that decreases the probability of East workers drawing offers from the West, fewer flows of East workers towards West firms could alternatively be driven by East workers being more likely − relative to West workers − to sample from the left tail of the offer distribution, rather than randomly. While this is a strong assumption, it does not affect the overall message of our results, but it does require more nuance in the interpretation: in practice, whether workers receive fewer or worse offers from the non-home region does not affect the presence of an overall bias in the offer received.

Second, the wage posting protocol implies that, within-firm, all workers are paid an identical wage per efficiency unit. As a result, within-firm wage differences directly map into productivity differences. This assumption is crucial to estimate the skill parameters θ_j^i. In fact, under different wage setting

Table 4: Estimation Targets, Model Fit, and Counterfactuals

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Data	Model	Taste Bias	Migration		Hiring Subsidy	
					Costs	Offers	Costs	Offers
	Average Wage Gains for Movers							
(1)	Moves from East to West (West-Born)	24.8%	27.4%	41.9%	12.8%	35.6%	27.3%	28.2%
(2)	Moves from East to West (East-Born)	44.7%	52.5%	44.0%	43.2%	49.5%	52.4%	55.4%
(3)	Moves from West to East (West-Born)	30.2%	22.1%	7.9%	12.4%	21.5%	22.5%	25.7%
(4)	Moves from West to East (East-Born)	0.7%	-4.9%	9.5%	-13.0%	9.3%	-4.5%	-4.2%
(5)	Moves Within West (West-Born)	19.6%	13.6%	13.5%	13.8%	15.0%	13.8%	14.0%
(6)	Moves Within West (East-Born)	15.1%	12.9%	13.2%	13.0%	13.5%	13.1%	13.1%
(7)	Moves Within East (West-Born)	10.1%	12.1%	12.6%	11.9%	13.1%	12.2%	12.8%
(8)	Moves Within East (East-Born)	11.1%	12.2%	12.5%	12.4%	13.6%	12.4%	13.0%
	Rates of Job-Job Mobility							
(9)	Moves from East to West (West-Born)	0.074%	0.079%	0.026%	0.191%	0.483%	0.080%	0.097%
(10)	Moves from East to West (East-Born)	0.021%	0.005%	0.014%	0.015%	0.288%	0.005%	0.007%
(11)	Moves from West to East (West-Born)	0.003%	0.002%	0.009%	0.007%	0.071%	0.002%	0.002%
(12)	Moves from West to East (East-Born)	0.058%	0.046%	0.019%	0.067%	0.138%	0.046%	0.056%
(13)	Moves Within West (West-Born)	1.291%	1.043%	1.004%	1.059%	0.689%	1.052%	1.300%
(14)	Moves Within West (East-Born)	1.351%	1.161%	1.217%	1.161%	0.599%	1.173%	1.451%
(15)	Moves Within East (West-Born)	1.174%	0.85%	0.920%	0.82%	0.615%	0.085%	1.051%
(16)	Moves Within East (East-Born)	1.108%	1.116%	1.125%	1.117%	0.939%	1.121%	1.439%
	Regional Employment Rates							
(17)	Share of West-Born working in West	97.0%	97.0%	77.6%	96.7%	85.9%	97.4%	97.6%
(18)	Share of East-Born working in East	83.9%	84.2%	52.7%	74.4%	35.1%	83.2%	86.1%
(19)	Unemployment Rate in West Germany	7.0%	6.8%	7.8%	6.6%	6.6%	6.6%	4.7%
(20)	Unemployment Rate in East Germany	11.9%	11.3%	10.3%	10.9%	9.9%	11.0%	7.9%
	Within Region Joint Distribution of Wages-Size							
(21)	Employment in 10% Largest Firms (W)	58.3%	75.6%	72.9%	75.4%	86.4%	75.4%	82.1%
(22)	Employment in 10% Largest Firms (E)	54.4%	62.4%	64.1%	62.1%	69.8%	62.0%	70.8%
(23)	Skewness of Labor Distribution (West)	0.78	0.70	0.87	0.76	1.12	0.73	0.86
(24)	Skewness of Labor Distribution (East)	0.70	0.82	0.82	0.85	0.76	0.85	0.90
(25)	Firm's Size-Wage Premium (West)	12.5%	11.4%	11.7%	11.4%	10.6%	11.4%	11.2%
(26)	Firm's Size-Wage Premium (East)	11.5%	12.2%	12.1%	12.2%	12.3%	12.2%	12.9%
	Regional Wage and GDP Gaps							
(27)	West-East Gap in Firm wage	16.9%	14.0%	12.8%	13.7%	19.4%	14.0%	14.8%
(28)	West-East Gap in GDP per worker	24.6%	28.8%	15.5%	23.3%	21.5%	24.4%	24.4%

Notes: The table shows the estimation targets and the model generated moments. Columns (1) and (2) present the moments in the data and in our benchmark model. Columns (3)-(5) present the moments when we shut down various spatial frictions. Columns (6)-(7) shows the moments with general hiring subsidies.

methods, the estimated low level of worker effects for East-born workers could represent some type of discrimination from firms, rather than a lower level of human capital. A similar argument applies for the comparative advantage: it could represent a higher pay per efficiency unit in the home region. Overall, we are not primarily concerned about this assumption, due to the fact that it turns out, empirically, that skill differences are not a main driver of spatial barriers, and thus are not a central aspect of our paper.

5.4   Estimation Results and Model Fit

Columns (1) and (2) of Table 4 compare the empirical targets to the moments generated by the estimated model. The model provides a fair fit to the data, especially considering that we are using 13 parameters to target 28 moments.[42] Importantly, the model replicates the key moments driving the identification: East-born have larger wage gains moving West and a lower probability of doing so than West-born while working in the East, and the opposite holds true for moves from West to East. Moreover, the wage gains resulting from a move across regions are, on average, significantly larger than those associated with a move within regions.

The fact that our model generates the key empirical patterns builds confidence in the validity of our estimated parameters. The four key parameters of interest are in rows 11 to 14 of Table 3 and show that: i) workers value one dollar earned while in the foreign region as 95.1 cents earned in their home region; ii) a move across regions costs 3.38% of the present discounted value of future earnings, or approximately 17,000 euros;[43] and iii) workers are more likely to receive offers from the region they are currently working in than from the other one, yet the difference is not as large as the one in rates of job-job mobility within and across regions, implying that workers reject more across-region offers.

At the same time, we recognize that the fit of the model is, as often, not perfect. The model fails where expected. In particular, it overestimates the wage gains of workers moving towards the West and the gap in GDP per worker. Firms in the West are more likely to be on the high rungs of the Germany-wide labor ladder, and thus effectively enjoy more monopsony power. They therefore lower their wages relative to their productivity (Gouin-Bonenfant (2018)). Since we tied our hands by not allowing the value of unemployment or the search intensity of the unemployed to be relatively higher in the West than in the East, the estimation will target the East-West wage gap through one of two mechanisms: i) by increasing the productivity gap, Z, at the cost of overshooting the regional GDP gap or ii) by reducing the amenity value, τ_W, of living in the West, making the individual-level wage gains from moving West too high. Overall, we are not too worried by these discrepancies since they are unlikely to affect the core parameters of interest, which are mostly estimated out of the asymmetries between moments for East- and West-born workers. Nonetheless, they lead us to be cautious in the

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[42]A simple way to quantify the fit of the model is to compute the average percentage deviation of the model from the data implied by the value of the objective function evaluated at ϕ^*. We find $\mathcal{L}(\phi^*) \approx 1$, which implies that model moments deviate from the empirical ones by, on average, $\pm 15\%$.

[43]Back of the envelope calculation: at an average salary of 2,500 euros per month, the present discounted value of future earnings, using $r = 0.005$ (monthly) as in the our calibration, is 500,000 euros. 17,000 is 3.38% of 500,000 euros.

interpretation of Z and τ_W.

Shutting Down Spatial Barriers. Next, we recompute the model keeping all parameters constant, but shutting down, one by one, the three sources of spatial barriers. Results are in Table 4: in column (3), we set the taste bias equal to 0, i.e. we let $\tau_h = 1$; in column (4), we shut down the migration cost, i.e. we set $\kappa = 0$; in column (5), we set the offer bias equal to 0, i.e. we let $\varphi_{hf} = \varphi_{fh} = 1$. The goal of this exercise is to build some further intuition for the magnitude of the results and to validate the heuristic identification argument.

Shutting down the taste bias eliminates the main sources of asymmetry in cross-regional wage gains since East- and West-born now accept a similar set of offers. The asymmetry in regional flows is also reduced, but still remains due to the presence of the offer bias, which distorts the opportunities to migrate. Finally, we notice that workers are much less likely to be employed in their home region since they assign the same value to both regions.

Eliminating the migration cost has very different implications. It does not affect the asymmetry between East- and West-born, but it reduces across the board the wage gains of cross-regional moves since workers are willing to accept lower wage offers. At the same time, a gap between cross- and within-region wage gains remains, due to the presence of taste bias and the difference in the distributions from which the offers are sampled. The cross-regional flows are much larger, but the effect on workers' employment location is muted: workers climb a cross-regional ladder, but taste and offer bias distort this ladder since the workers are constantly attracted to their home region.

The offer bias mostly affects, as expected, the cross-regional labor market flows. Setting $\varphi_{hf} = \varphi_{fh} = 1$, and thus making workers equally likely to be contacted by any firm irrespective of their current region, leads cross-regional flows to increase steeply. The remaining difference in flows is due to the presence of taste bias and migration cost, which reduce the probability that cross-regional offers are accepted.

Finally, we notice, in row (27), that removing any one of the three sources of spatial barriers has at most modest effects on the regional gap in firms' wage rates. Two reasons drive this result: i) the model rationalizes the observed wage (and GDP) gap to a large extent through differences in productivity, which are unaffected by the frictions; and ii) while firms in West Germany are, on average, more productive, there is a lot of overlap in the productivity distributions of the two regions. Consider for example the effect of shutting down the taste bias (Column (3)). Eliminating this bias leads East firms to increase their wages and low wage firms in the East to shrink, since East firms are now exposed to stronger competition from the West for East-born workers.[44],[45] Nevertheless, due to the large overlap in the productivity distributions and since most offers are received within region, the effective increase in labor competition is modest. As a result, there is only a minor increase in East firms' relative wages. The results on the GDP gap, in row (28), generally mirror those for the wage gap. While shutting

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[44]While the home bias is equally large for East- and West-born, there are relatively more East-born workers with respect to East-firms, thus implying that the effect of the home bias on local labor supply is larger for East firms.

[45]Reallocation of labor within the East can be seen in row (22).

down the taste bias appears to have a comparatively large effect on the GDP gap, this effect is mainly driven by the fact that the less skilled East-born workers are now more uniformly distributed across space.

5.5   Aggregate Implications

Table 5 presents the aggregate effects of removing the three frictions. Column (1) shows the main aggregate statistics computed with the baseline estimated model. Column (2) shows that removing the taste bias actually leads to a reduction in GDP and average wages. Intuitively, firms in the West are now able to more easily attract East German workers, which causes them to lower their wage. While East firms are now exposed to more competition for workers and raise their wage, overall the wage reduction in the West dominates, and the average wage level falls. However, in utility terms, workers gain on average because they no longer suffer a utility loss while employed away from home.

In practice, removing the taste bias is not a feasible policy. We therefore next compare two policy approaches that a government could implement: i) *migration subsidies* aimed at fostering regional integration; ii) equally costly *hiring subsidies* aimed at fostering overall labor mobility and reallocation across firms without any specific regional directive. We show that, through the lens of our model, the latter provide larger benefits.

Migration Subsidies. We consider two types of migration subsidies, along the lines of removing the spatial frictions discussed earlier. First, we consider a transfer paid to workers upon a migration from one region to the other that exactly compensates them for the migration cost, which is equivalent to setting $\kappa = 0$. Second, we endow the government with the ability of posting vacancies directed at worker-region types, and consider a subsidy, in terms of vacancies, that matches any vacancy posted by a firm so that the overall contact rate to workers in each region is equal to 1.[46] This subsidy is equivalent to setting $\varphi_{hf} = \varphi_{fh} = 1$.

We already discussed the effects of these two migration subsidies for the targeted moments (Table 4). Additionally, columns (3) and (4) of Table 5 show that both policies increase aggregate GDP and the average wage. While workers are still relatively attracted to their home region, the policies allow workers to climb a more integrated, country-wide job ladder, which improves the allocation of labor to firms. The effect of the policies on welfare, as measured by the average flow utility of workers, is smaller. The migration subsidies lead more workers to be employed away from their home region, and thus the benefit from higher wages is attenuated by the taste bias. In fact, compensation for the migration cost leads the average utility of East-born workers to slightly decrease, even as their average wage increases steeply.

We also notice that the second subsidy has a much larger effect on GDP. Mechanically, this outcome is driven by the large effect on the concentration of labor, which can be seen in rows (21) and (22) of

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[46]Recall that firms cannot post region- or type-specific vacancies. In fact, vacancies are general, and then they reach workers in different regions according to an estimated exogenous wedge φ_{jx}^i.

Table 4.[47] The two subsidies, however, should not be directly compared since they have very different costs. The first subsidy costs only 0.021% of baseline aggregate GDP, since i) even when the migration cost is fully subsidized workers do not move frequently across regions due to taste and offer biases; ii) the estimated migration cost that is subsidized is small. The second subsidy, on the other hand, is extremely expensive, costing 24.11% of the baselined aggregate GDP. The high price-tag is due to the convexity of the vacancy cost: at baseline, the overall cost of posting vacancies is 3.86% of aggregate GDP; the migration subsidy increases overall vacancies by approximately 50%, but the cost of posting these additional vacancies is very high.

Hiring Subsidies. Next, we consider two types of hiring subsidies, designed to be as costly as the two migration subsidies just described, but not targeted towards regional integration.

First, we consider a subsidy, ϖ, that decreases the cost of posting vacancies faced by firms. We calibrate ϖ such that the overall cost of the subsidy is the same as the cost of the first migration subsidy discussed above, i.e., the cost of compensating workers for their migration cost, at that equilibrium outcome. Second, we let the government post additional vacancies to increase the contact rate of each vacancy posted by a scalar ρ.[48] We calibrate ρ such that the total number of posted vacancies is the same as the ones posted in the second migration subsidy discussed earlier.[49]

The results for both hiring subsidies are shown in columns (5) and (6) and paint a similar picture. The hiring subsidies have similar effects as the migration subsidies in terms of aggregate GDP and wages. However, they lead to larger gains in terms of utility.

The results in this section highlight that it is important to take into account the workers' preference for their home-region when designing labor market policies. By separating home region preferences from general migration costs, we are able to show that workers suffer a sizable utility cost when employed away from home. As a result, policies fostering reallocation of labor within local labor markets may dominate policies promoting regional integration since the former do not incur the utility cost of having workers employed away from their home region.

5.6 Three General Takeaways

While the magnitude of the results is specific to this context, we learn from the analysis three lessons of general interest.

First, we show that, in frictional labor markets, a large regional wage gap and wage gains from migration can be supported in equilibrium by relatively small migration frictions. Even when controlling

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[47]The first subsidy has no effect on the concentration of labor in the top 10% of the firms. Intuitively, the very best firms are relatively unaffected by the migration cost subsidy, since they pay a wage which is sufficiently high to make the migration cost less relevant. Therefore, this subsidy only affects aggregate GDP through: i) decrease in the unemployment rate; ii) increase in the labor concentration below the top 10%. The second subsidy also affects the hiring of the top 10% of firms directly. Since the firms are the largest in the economy, the aggregate effects are large.

[48]The overall contact rate increases, but the regional bias is unaffected.

[49]Appendix D.3 presents the equations for the budget constraints for both hiring subsidies.

Table 5: Aggregate Role of Spatial Frictions and Subsidies

		(1)	(2)	(3)	(4)	(5)	(6)
		Model	Taste Bias	Migr. Subsidy		Hiring Subsidy	
				Costs	Offers	Costs	Offers
				Percentage Deviation From Benchmark			
(1)	Aggregate GDP	-	-1.25%	+0.46%	+13.24%	+0.18%	+12.21%
(2)	Average Wage	82.0%	-1.31%	+0.47%	+13.94%	+0.18%	+12.69%
(3)	Average Firms' Profits	18.0%	-0.94%	+0.41%	+10.04%	+0.15%	+10.07%
(4)	Average Flow Utility	-	+0.85%	+0.01%	+9.14%	+0.06%	+10.48%
(5)	Average Wage of W-Born	-	-8.49%	+0.07%	+6.50%	+0.38%	+11.72%
(6)	Average Wage of E-Born	69.0%	+3.48%	+0.75%	+18.90%	+0.05%	+13.33%
(7)	Average Flow Utility of W-Born	-	+1.66%	+0.05%	+10.09%	+0.07%	+9.86%
(8)	Average Flow Utility of E-Born	75.8%	+0.36%	-0.01%	+8.57%	+0.05%	+10.85%
(9)	GDP per Efficiency Unit, West	-	-1.32%	-0.33%	+12.03%	-0.08%	+8.10%
(10)	GDP per Efficiency Unit, East	86.0%	+1.43%	+0.24%	+8.06%	+0.05%	+8.47%

Notes: Column (1) presents aggregate statistics computed with the baseline estimated model. Since the level of GDP and the aggregate utility do not have interpretable units, we normalize the average wage and average profits (Rows (2) and (3)) as a share of GDP per capita, and the average wage of E-born, average flow utility of E-born, and average GDP per efficiency unit of E-born (Rows (6), (8), and (10)) as shares of their W-born equivalents. Columns (2)-(6) present the change in each aggregate statistic relative to the baseline, where each variable is still normalized using the values from the baseline case. GDP and wages are expressed in units of the tradable good in order to not be affected by price deflators. The flow utility, instead, depends on the regional price deflators.

for observable characteristics, we have shown that real wages in the West of Germany are more than 25% larger than those in the East. Further, East-born workers moving West have on average a wage increase larger than 40%. A simple arbitrage argument would lead us to conclude that there must exist equally sized frictions preventing labor to move West. Our structural analysis, instead, shows that the one-time cost of moving from East to West is only about 3.4% of present discounted earnings, and East-born workers pay an implicit "taste-tax" equal to another 5% of their earnings. Even adding these two frictions, we are still far from the arbitrage value, and significantly below previous estimates from the literature, such as the $312,000 inter-state migration cost estimated for the United States in Kennan and Walker (2011).

Second, we show the importance of distinguishing between different types of spatial frictions, and of building an empirical framework to estimate their magnitudes. In our context, we have found that migration costs and home bias have similar size, yet they have different implications. On the one hand, home bias is more relevant in determining the persistent effects of birth-place on individual earnings and location, since it causes workers to frequently return home. On the other hand, migration frictions prevent workers from climbing a country-wide ladder and thus worsen the allocation of workers to firms. Furthemore, we have shown that the two types of frictions interact with each other, shaping the returns of different policy interventions. Migration subsidies aimed to foster regional integration

Figure 6: Wage-Size Ladder in the Model and in the Data

(a) Model (No Spatial Frictions / Amenity Differences)

(b) Model (Baseline)

(c) Data
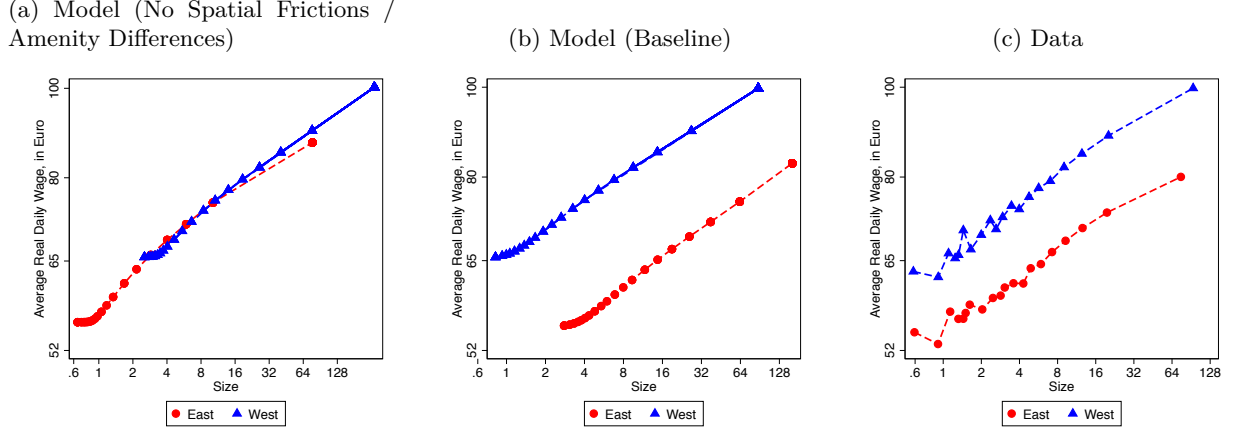
have negligible welfare effects due to the sizable utility cost incurred by workers employed away from home. Instead, general hiring subsidies can have larger welfare effects since they lead to within-region reallocation of labor from lower to higher productivity firms.

Third, we show that the observed cross-regional labor flows provide only a partial picture of the true regional integration of the labor market. In our context, we estimate that workers' skills are equally valued by firms in both regions, and that workers do receive a fair amount of offers from the region where they are not currently working. Yet, a large share of the offers are rejected due to migration costs and taste bias, thus leading to low cross-regional mobility. In other words, workers do have opportunities to move across regions, but they often choose not to take them.

5.7 Model Validation

We provide an external validation of the model by studying empirically the relationship between firm size and wage. Recall that in our model a wage gap between regions can persist even in the absence of spatial frictions if there is a productivity gap between regions and reallocation frictions that make it difficult for workers to move. However, the model predicts that if spatial frictions are present, then there must be a wage gap conditional on firm size. Figures 6a-6b illustrate this point. Figure 6a shows in the model the wage functions of firms in the East and in the West, respectively, in the absence of spatial frictions and price/amenity differences. These lines are on top of each other: without spatial frictions nor amenity differences the location of a firm does not matter, and therefore two firms posting the same wage will attract the same mass of workers in equilibrium. However, since the productivity distribution in the West is shifted to the right, the wage distribution in the West has a longer right tail. Workers cannot take full advantage of these higher wages since frictions make it necessary to wait for a job offer from these top firms. As a result, there is a gap in the average wage between the two regions. Figure 6b presents the case with spatial frictions between East and West. In this case, firms in each region are partially shielded from competition by firms in the other region. Specifically,

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since the average productivity in the West is higher, firms in the West have to post a higher wage to attract the same number of workers. As a result, conditional on size, West firms post higher wages. We empirically confirm this sign of spatial frictions in the data. Figure 6c plots the average wage by size bin separately for East and West firms: for any establishment size, West German firms pay a higher real wage, thus confirming a central implication of our model.[50]

6 Interpretation of Workers' Home Bias

Our results have so far highlighted the importance of distinguishing between home bias and migration costs. At the same time, they are necessarily silent on the deep drivers of home bias, and therefore on whether policy may mitigate or affect the home bias. We next use additional sources of empirical variation to shed light on three factors that likely modulate the strength of the home bias. We first highlight the importance of family ties by studying the return migration propensity after the birth of a child. We then follow the literature on migration and show that workers are relatively more attracted to counties with a large presence of individuals with similar cultural identity. Finally, we separate the role of regional identity (East vs West) from the role of state identity (e.g. Bavaria vs Hamburg) and we show that both have an independent role. Yet, on the aggregate, the regional identity is more relevant since it interacts with large productivity differences.

6.1 The Importance of Family Ties

We examine the role of child birth on workers' mobility by exploiting the fact that the SOEP records whether individuals have a child. Using the "Old SOEP Sample", we focus on the sub-sample of full-time workers that are employed at time t in their non-native region and run

$$Migr_{it} = \alpha + \sum_{\tau=-3}^{3} \beta_\tau \mathbb{D}_\tau + \epsilon_{it}, \tag{22}$$

where $Migr_{it}$ is a dummy that is equal to one if worker i moves back to her home region at time t, and $\mathbb{D}_\tau$ are dummies around a child birth event (at $\tau = 0$).[51] Figure 7a shows the estimated coefficients for East-to-West return moves of West-born workers, while Figure 7b presents the coefficients for West-to-East return moves of East-born workers. We find a significant spike of return moves one year after the birth of a child, thus suggesting that young parents might be more willing to move back home, possibly to benefit from childcare support from their own parents. The finding suggests that familial ties may be important in explaining workers' attachment to their home region.

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[50]In practice, we use data from BHP and we residualize both wages and sizes as described in Section 5.3 and then add the overall region-specific means.

[51]The new SOEP sample only has an extremely small number of child births, which does not allow us to run this regression in that sample.

Figure 7: Child Birth Event Study

(a) East to West Return Move Probability

(b) West to East Return Move Probability
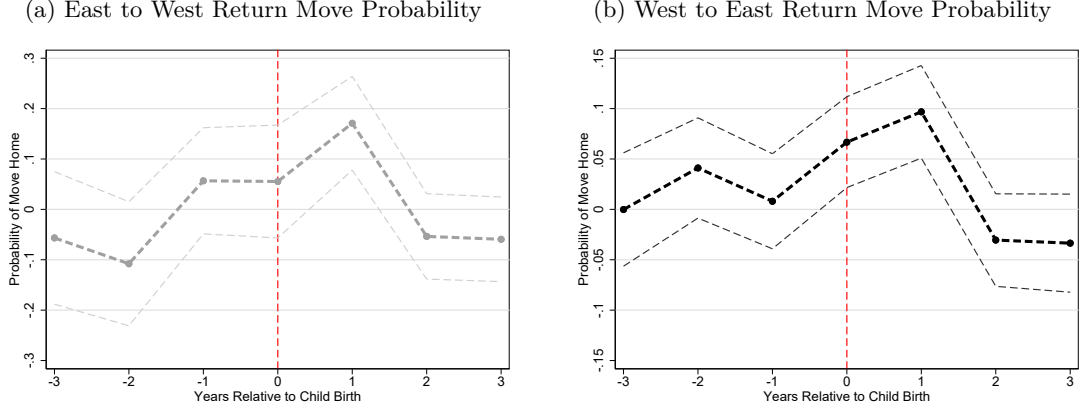
6.2 The Role of Ethnic Enclaves

We next show that East-born migrants are more likely to move to counties already containing a significant number of East-born individuals. As documented in Burchardi and Hassan (2013), in the years 1946 to 1961 several million individuals fled to West Germany after having spent several years in the East to preempt the construction of the wall. These "East-tied" individuals were more likely to settle in counties with available houses. We can replicate the same identification strategy as in Burchardi and Hassan (2013) and use housing destruction due to WWII as an instrument for the inflow of these individuals, with migration flows as dependent variable. Columns (1) and (2) of Table 6 regress the gaps in the destination and origin fixed effects from regression (3) on the instrumented inflows of East-tied individuals.[52] Coefficients are normalized in terms of standard deviations.

The results have the expected sign – counties in the West that exogenously received more East-tied individuals before 1961 are also relatively more attractive for East-born individuals in 2009-2014. The coefficients are large in magnitude; however, they are either non-significant (Column 1) or marginally significant (Column 2). Since the gap between East-born and West-born fixed effects is likely to be measured with significant noise, in Columns (3) and (4) we replicate the same analysis using only the county fixed effects for East-born workers as the dependent variable, and controlling for the fixed effects of West-born workers. The point estimates are comparable and now have stronger statistical significance. The large and positive coefficients on the West-born fixed effects indicate that East- and West-born fixed effects are highly correlated, consistent with workers from both regions assigning the same ranking to counties of a given region.

This result is consistent with the large migration literature (e.g. Edin, Fredriksson, and Åslund (2003)) showing that ethnic connections have an important role in determining labor market success. In our context, it is consistent with East-born either having more job opportunities due to tighter social connections with East German refugees (offer bias), or East-born preferring to work in areas

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[52]The exact variable is the share of expellees through the Soviet Sector. See Burchardi and Hassan (2013) for details.

Table 6: Current Attraction of East-born Workers to Counties with High East-Tied Inflows

	(1)	(2)	(3)	(4)
	$\gamma_d^E - \gamma_d^W$	$\delta_o^E - \delta_o^W$	γ_d^E	δ_o^E
Share Expellees (Sov. Sec.) '61	.2877	$-$**.5865***	.4482	$-$**.5552****
	(.3984)	(.3507)	(.3047)	(.2756)
Log Income p.c. 1989	$-$.1711	.0678	$-$.0544	$-$.0015
	(.1047)	(.0922)	(.0790)	(.0715)
Distance to East	.0177	$-$.0624	.0990	.0153
	(.1238)	(.1090)	(.0949)	(.0846)
γ_d^W			**.5490*****	
			(.0491)	
δ_o^W				**.6164*****
				(.0447)
State FE	Y	Y	Y	Y
Observations	291	291	291	291

Notes: $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively.

where other East Germans live (taste bias).

6.3 State or Regional Identity?

Finally, we consider worker flows not only across regions but also across federal states in Germany. This exercise allows us to understand whether the home bias is mostly due to the different cultural heritage of East Germany or whether there is an independent, and more localised, state identity.

We re-run the cross-county mobility regression with dummies (equation 4), but in addition to the three dummies for cross-border moves ($\mathbb{I}^{R(o)\neq R(d)}$), moves to a county in the home region ($\mathbb{I}^{R(d)=h}$), and moves away from the home region ($\mathbb{I}^{R(o)=h}$), we add three additional dummies for moves across states ($\mathbb{I}^{S(o)\neq S(d)}$), moves to a county in the home state ($\mathbb{I}^{S(d)=h}$), and moves away from the home state ($\mathbb{I}^{S(o)=h}$), where S denotes federal states and h refers to the home region or home state. We determine home states analogously to home regions. Let $\mathbb{K} = \{R(o) \neq R(d), R(o) = h, R(d) = h\}$ and $\mathbb{M} = \{S(o) \neq S(d), S(o) = b, S(d) = h\}$ capture these possibilities. We thus run:

$$\log s_{o,d}^h = \delta_o + \gamma_d + \mu^h + \sum_{x \in \mathbb{X}} \phi_x D_{x,o,d} + \sum_{k \in \mathbb{K}} \beta_k \mathbb{I}_{it}^k + \sum_{m \in \mathbb{M}} \gamma_l \mathbb{I}_{it}^l + \epsilon_{o,d}^h, \tag{23}$$

Column (1) of Table 7 presents the results. We find that there is a significant bias towards the home state. However, even after accounting for the home state effect, there is still a sizable regional home bias. While we find a small negative effect of crossing a state or regional border, these effects are significantly smaller than the home state or region bias.

Table 7: States Versus Regions

	(1)		(2)
	Flows	Wages	
$\mathbb{I}_{it}^{(R(o)\neq R(d))}$	$-.1527^{***}$	$d_{it}^{EW,m}(\mathbb{I}_i^{East}=0)$	$.1942^{***}$
	$(.0072)$		$(.0268)$
$\mathbb{I}_{it}^{(R(o)=h)}$	$-.7955^{***}$	$d_{it}^{WE,m}(\mathbb{I}_i^{East}=0)$	$.1033^{***}$
	$(.0782)$		$(.0313)$
$\mathbb{I}_{it}^{(R(d)=h)}$	0.5000^{***}	$d_{it}^{EW,m}(\mathbb{I}_i^{East}=1)$	$.2320^{***}$
	$(.0769)$		$(.0168)$
		$d_{it}^{WE,m}(\mathbb{I}_i^{East}=1)$	$.0335$
			$(.0204)$
$\mathbb{I}_{it}^{(S(o)\neq S(d))}$	$-.2037^{***}$	$\mathbb{D}_{it}^{(S(o)\neq S(d))}$	$.0325^{***}$
	$(.0083)$		$(.0105)$
$\mathbb{I}_{it}^{(S(o)=h)}$	-2.6677^{***}	$\mathbb{D}_{it}^{(S(o)=h)}$	$.1070^{***}$
	$(.0060)$		$(.0135)$
$\mathbb{I}_{it}^{(S(d)=h)}$	0.7499^{***}	$\mathbb{D}_{it}^{(S(d)=h)}$	$-.0521^{***}$
	$(.0060)$		$(.0146)$
DiD Migr			$-.108$
Observations	$94,203$		$6,122,208$

Notes: $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively.

We similarly examine wage gains by re-running the wage gain regression (2) for the year of the move ($\tau = 0$) but add three dummies for moves across states ($\mathbb{D}^{S(o)\neq S(d)}$), cross-state moves that are back to the home state ($\mathbb{D}^{S(d)=h}$), and cross-state moves away from the home state ($\mathbb{D}^{S(o)=h}$). The first four rows of Column (2) show that, even after controlling for state, workers still obtain significant wage gains when leaving their home region. The last three rows highlight that in addition to regional home bias, there is also a strong state home bias: workers receive significant wage gains when leaving their home state.

Overall, home bias is clearly present even across states within East and West Germany, rather than solely between the two regions. This finding leads us to conclude that the home bias we documented in this paper is likely a phenomenon that is not only the result of the historic circumstances particular to Germany and the long-time separation between East and West Germany.

There are several other plausible sources of home bias that we have not explored empirically. For example, workers could be reluctant to move due to homeownership and an illiquid housing market (Head and Lloyd-Ellis (2012)), or benefit from informal insurance arrangements in their home region (e.g., Guvenen and Smith (2014), Munshi and Rosenzweig (2016)). Workers could also have access to more attractive housing options in their home region (Lagakos, Mobarak, and Waugh (2018)).

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7 Conclusion

In this paper, we use matched employer-employee data from Germany to carefully measure the frictions contributing to the lack of workers' mobility across space. Our approach yields three insights: first, we show that a large regional wage gap and wage gains from migration can be supported in equilibrium by relatively small migration frictions, given cross-regional differences in firm productivity and a frictional labor market. Second, we argue that it is important to distinguish, and separately estimate, different types of spatial frictions, such as home bias and migration costs. We show that, once the utility cost of moving away from home is taken into account, migration subsidies provide smaller welfare gains than equally expensive hiring subsidies that foster the within-region reallocation of labor. Finally, we argue that it cannot be concluded from a lack of flows across regions that the labor market is not integrated. In the example of Germany, workers receive many opportunities to migrate to the other region, yet they choose not to accept most of them.

Our paper suggests several avenues for future research. First, our work has focused on the frictions that hinder worker mobility, taking the distribution of firms as given. The presence of this sizable productivity gap raises the question, given the lack of worker migration, why West German firms do not move East. Part of the answer may lie in network effects, as pointed out by Uhlig (2006). However, a more thorough investigation of firms' location choice in Germany would be useful to understand the persistence of the East-West wage gap. Second, our paper has developed a theory of a frictional labor market that can easily be embedded into richer models of the geography of trade in the goods market, such as Caliendo, Dvorkin, and Parro (2019) and Caliendo, Opromolla, Parro, and Sforza (2017). Our model can therefore be used to study more thoroughly the quantitative effects of trade shocks taking into account the response of the labor market, or to analyze the interplay between spatial frictions in the goods and labor market.

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Appendix

A   Historical Overview

East and West Germany were separate countries before 1990. There was virtually no movement of workers between the two regions, and the border was tightly controlled. This separation gave rise to two distinct economic systems. While West Germany was a market economy, the economy in East Germany (then called the German Democratic Republic, GDR) was planned.

The German reunification completely removed the East German institutions of the planned economy and replaced them with West German ones. Starting on July 1, 1990, the two Germanys started a full monetary, economic, and social union, and introduced the regulations and institutions of a market economy to the GDR. These included for example the West German commercial code and federal taxation rules, as well as a reform of the labor market which imposed Western-style institutions (Leiby (1999)). At the same time, the West German Deutschmark (DM) became the legal currency of both halves of Germany. Wages and salaries were converted from Ostmark into DM at a rate of one-to-one, as were savings up to 400DM. While the currency reform implied an East German wage level of about 1/3 the West German level, in line with productivity, the switch meant that East German firms lost export markets in Eastern Europe, since customers there could not pay in Western currency. Additionally, East German customers switched to Western products, which were of much higher quality than East German ones (Smolny (2009)). West German unions negotiated sharp wage increases in many East German industries, which were not in line with productivity gains but driven by a desire to harmonize living conditions across the country (Burda and Hunt (2001), Smolny (2009)). As a consequence, East German unit labor costs rose sharply, and output and employment collapsed (Burda and Hunt (2001)). This trend was further exacerbated by the break-up and transfer of unproductive East German conglomerates to private owners, who usually downsized or closed plants.[53]

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[53]This transfer was done via the *Treuhandanstalt*, a public trust, which was set up by the West German government to manage and ultimately sell the GDR's public companies. West German were initially slow to invest into East German firms. Eventually, most firms were sold at very steep discounts to the highest bidder, usually West German firms, which were often motivated by subsidies and had little interest in keeping their acquisitions alive (Leiby (1999)).

B   Empirical Exercises

B.1   Growth Accounting

West German GDP per capita in real terms (adjusted for cost of living differences as in the main text) is still around 40% larger than in the East (Figure 8). We perform a standard accounting exercise to decompose this GDP gap into its different components. We follow the literature and assume an aggregate Cobb-Douglas production function, with elasticities to labor and capital equal to $1 - \alpha$ and α, respectively. We set, as usual, α equal to $\frac{1}{3}$. Aggregate GDP in the East and the West, respectively, in year t are therefore given by

$$
\begin{aligned}
Y_{E,t} &= A_{E,t} K_{E,t}^{\alpha} L_{E,t}^{1-\alpha} \\
Y_{W,t} &= A_{W,t} K_{W,t}^{\alpha} L_{W,t}^{1-\alpha},
\end{aligned}
$$

where we observe in the data provided by the statistics offices of the states, for each year and separately for East and West Germany, capital K and GDP Y, and similarly we obtain from the Federal Employment Agency the total number of employed, L.[54] We can then use the previous formula to compute the implied total factor productivity term, A. We rewrite the previous equations in per capita terms, that is

$$
\begin{aligned}
y_{E,t} &= A_{E,t} k_{E,t}^{\alpha} l_{E,t}^{1-\alpha} \\
y_{W,t} &= A_{W,t} k_{W,t}^{\alpha} l_{W,t}^{1-\alpha},
\end{aligned}
$$

where $y \equiv \frac{Y}{N}$, $k \equiv \frac{K}{N}$, $n \equiv \frac{L}{N}$ and N is total population, also provided by the statistics offices of the states. Last, we decompose the percentage difference in GDP per capita between West and East into its three components, that is

$$
\underbrace{\log y_{W,t} - \log y_{E,t}}_{\text{GDP p.c. gap}} = \underbrace{\log A_{W,t} - \log A_{E,t}}_{\text{TFP gap}} + \underbrace{\alpha \left(\log k_{W,t} - \log k_{E,t} \right)}_{\text{Capital p.c. gap}} + \underbrace{(1 - \alpha) \left(\log l_{W,t} - \log l_{E,t} \right)}_{\text{Workers p.c. gap}}.
$$

In Figure 9 we plot the GDP per capita gap (top left) along with each of the three gap components over time. If a gap component does not explain the overall GDP per capita gap, it will be close to zero. We find that the initial convergence in GDP per capita is both due to a convergence in capital per capita and in TFP. Both of these components start significantly above zero and then rapidly decline. However, virtually all of the current gap between East and West Germany is due to a lower level of TFP in East, as the capital gap is virtually zero by 2015. This result aligns with the better establishment component of West German establishments we find in our AKM decomposition in the main text, and hence the higher productivity we assign to West German establishments in the model.

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[54]We compute all statistics excluding Berlin to be consistent with the main text.

Figure 8: Real GDP per Capita
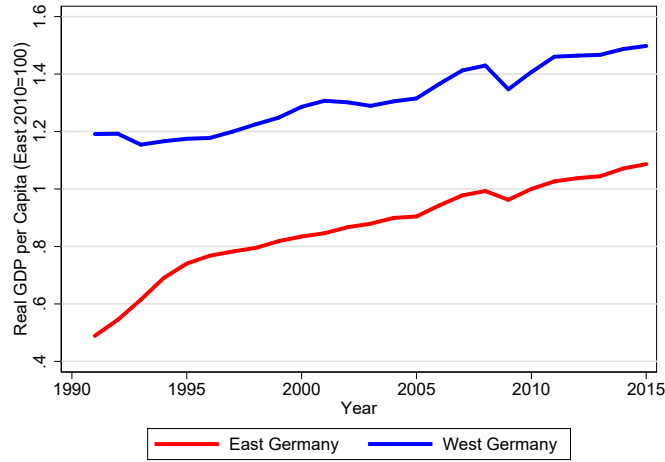
Sources: Volkswirtschaftliche Gesamtrechnungen der Laňder (VGRdL), BBSR. Notes: Excluding Berlin. Real GDP in 2010 prices obtained from VGRdL and divided by total population, then adjusted by the cost of living difference in 2007 from the BBSR.

Figure 9: Decomposition of the Real GDP per Capita Gap
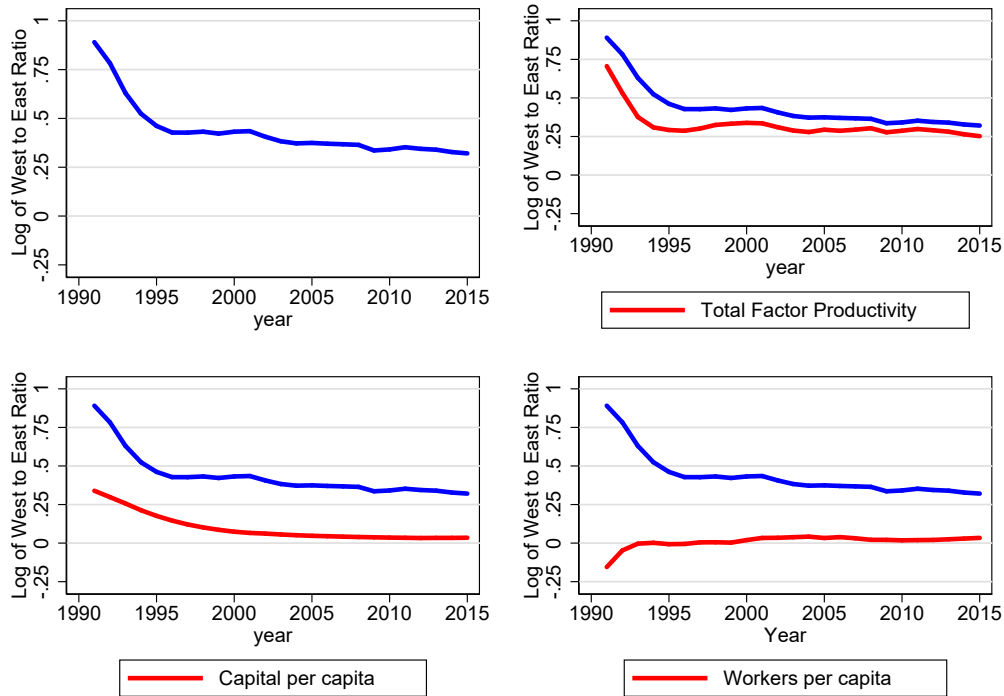
Sources: Volkswirtschaftliche Gesamtrechnungen der Länder (VGRdL), BBSR, Bundesagentur für Arbeit. Notes: Excluding Berlin. Top left panel shows log real GDP per capita gap between East and West Germany. GDP is obtained from VGRdL and divided by total population, then adjusted by the cost of living difference in 2009 from the BBSR and deflated by the deflator in the VGRdL. Top right panel shows log real GDP per capita gap together with TFP gap, where TFP is calculated as described in the text. Bottom left panel shows log real GDP per capita gap together with the gap in the real capital stock. Real capital stock is obtained as total net capital stock from VGRdL, deflated with the capital deflator, and adjusted for the cost of living difference in 2009 from the BBSR. Bottom right panel shows the log real GDP per capita gap together with the gap in the number of workers per capita, where workers per capita are calculated as all civilian dependent workers divided by the total population.

B.2 Taxes

There are a number of taxes in Germany. For most of these taxes, we do not find systematic differences between East and West Germany, as we show next.

First, the income tax and the value-added tax are the same anywhere in Germany.[55] Similarly, the corporate tax rate is the same.[56]

Second, all companies are subject to a business tax that is levied at the level of the individual community. The tax consists of the product of i) the business income, ii) a base rate, and iii) a leverage ratio. The business income is computed in the same way across Germany, and the base rate is 3.5% everywhere. The leverage ratio varies across communities. Figure 10a shows these leverage ratios and highlights that there are no systematic differences between East and West.

Third, the government collects taxes on behalf of the church. This church tax is higher in the South than in the North of Germany, but does not vary between East and West (Figure 10b).

Finally, property taxes are relatively low in Germany, accounting for about 0.44% of GDP in 2010, significantly lower than in most of the EU (Paetzold and Tiefenbacher (2018)). There are two types of property tax, Property Tax A (for agricultural properties) and Property Tax B (for everything else). The latter accounts for the vast majority of tax receipts from this income source. The property tax is calculated as the product of i) the property's "rateable value", ii) a base rate, and iii) a leverage ratio.[57] The rateable value is determined by a federal law on valuations. For West Germany, it is determined by a land census in 1964, while, due to the division of Germany, the rateable value for property in East Germany is mostly still based on the census from 1935. The base rate depends on the type of building, with different rates for example for residential property and agricultural property. It also differs across East and West Germany, with East Germany having on average higher base rates for similar types of properties. Finally, the leverage ratio is determined at the level of the individual community. We present the leverage ratios for the two types of property tax in Figures 11a and 11b, displayed in percent (e.g., 180 means a collection rate of 180%). While there are significant differences in ratios across communities, the ratios are not systematically different between East and West Germany.

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

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

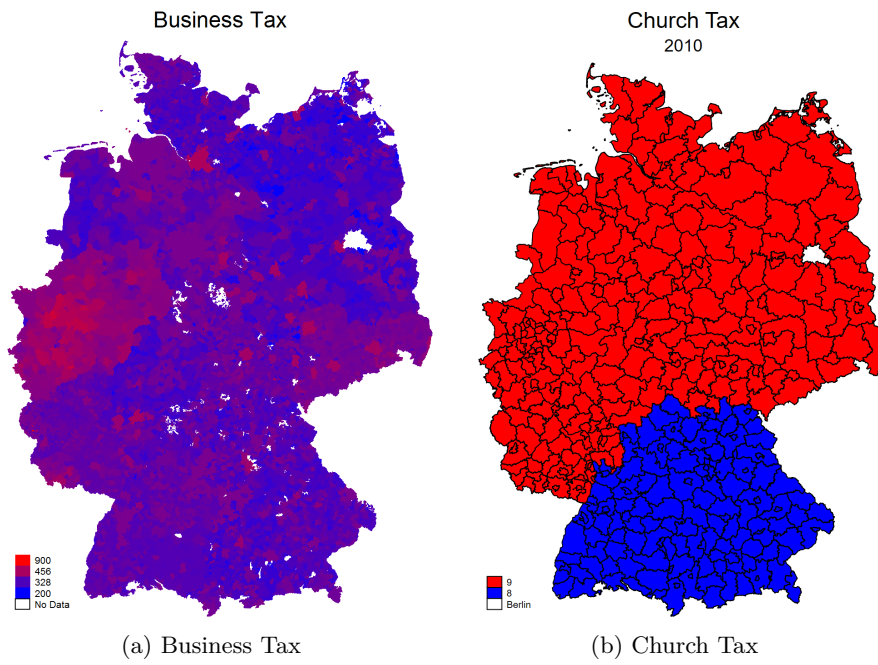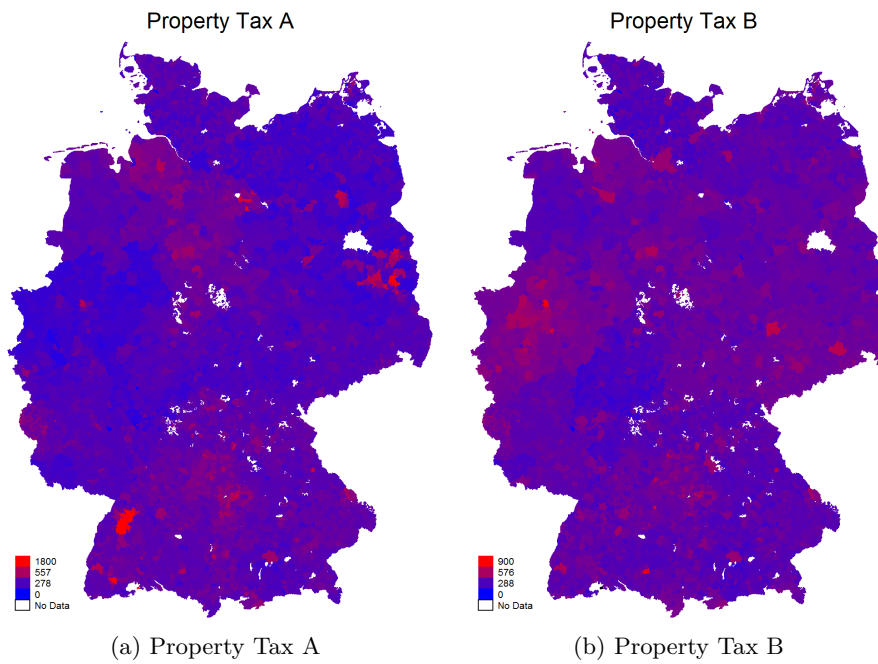[57]See Bird and Slack (2002).

Figure 10: Business Tax and Church Tax

Business Tax

Church Tax
2010

(a) Business Tax

(b) Church Tax

Figure 11: Leverage Ratios for Property Taxes

Property Tax A

Property Tax B

(a) Property Tax A

(b) Property Tax B

B.3 AKM Decomposition

Specification of the Baseline Model

We fit in the LIAB data a linear model with additive worker and establishment fixed effects, following Abowd, Kramarz, and Margolis (1999) and Card, Heining, and Kline (2013). The model allows us to quantify the contribution of worker-specific and establishment-specific components to the real wage gap. We implement equation (17) empirically as

$$w_{it} = \alpha_i + \psi_{J(i,t)} + \beta \mathbb{I}^{(R(h_i) \neq R(J(i,t)))} + B X_{it} + \epsilon_{it}, \tag{24}$$

where i indexes full-time workers, t indexes time, and $J(i,t)$ indexes worker i's establishment at time t.[58] Then α_i is the worker component, $\psi_{J(i,t)}$ is the component of the establishment j for which worker i works at time t, $\mathbb{I}^{(R(h_i) \neq R(J(i,t)))}$ is a dummy that is equal to one if worker i with home region $R(h_i)$ is currently employed at a firm in a different region, and X_{it} is a centered cubic in age and an interaction of age and college degree. We specify ϵ_{it} as in Card, Heining, and Kline (2013) as three separate random effects: a match component $\eta_{iJ(i,t)}$, a unit root component ζ_{it}, and a transitory error ϵ_{it},

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

In this specification, the mean-zero match effect $\eta_{iJ(i,t)}$ represents an idiosyncratic wage premium or discount that is specific to the match, ζ_{it} reflects the drift in the persistent component of the individual's earnings power, which has mean zero for each individual, and ϵ_{it} is a mean-zero noise term capturing transitory factors. As in Card, Heining, and Kline (2013), we estimate the model on the largest connected set of workers in our data.[59]

Identification of the Model with Comparative Advantage

We now discuss how we can identify the comparative advantage effect, β. Consider four wage observations associated with two workers: an East-born and a West-born individual working in one establishment in the East, and the same two individuals working in one establishment in the West. Figure 12a plots an example of these two workers' wages, where the x-axis is the identity of the establishment, the y-axis is the level of the wage, the inside coloring refers to the birth location of the worker, and the outside coloring refers to the location of the establishment. Figures 12b-12d then show how these data identify the three AKM components. First, as depicted in Figure 12b, the individual components are identified from comparing the wages of the two workers when employed at the same establishment. If a worker at a given establishment earns a higher wage than another, this worker is identified as having a higher individual component. Second, Figure 12c highlights that the establishment components are identified by comparing the same worker at two different establishments.

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

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

If the worker earns a higher wage at establishment X than at establishment Y, this difference is attributed to a higher establishment component of X. Finally, Figure 12d illustrates how the comparative advantage is identified. In the absence of comparative advantages, the two workers should have an identical wage gap between them in both establisments. We can thus identify the comparative advantage by comparing the wage differentials between the two workers when employed in the East- and in the West-establishment, respectively.

Note that the methodology cannot separately identify whether it is the East or the West-born worker that has a comparative (dis)advantage since all that is observed is their relative wage gap. For example, if the East German worker's wage is relatively lower than the West German's wage at an establishment in the West than at an establishment in the East, then this difference could either arise because the East-born worker has a relative disadvantage in the West or because the West-born worker has a relative disadvantage in the East.

Figure 12: Identification of the AKM Components
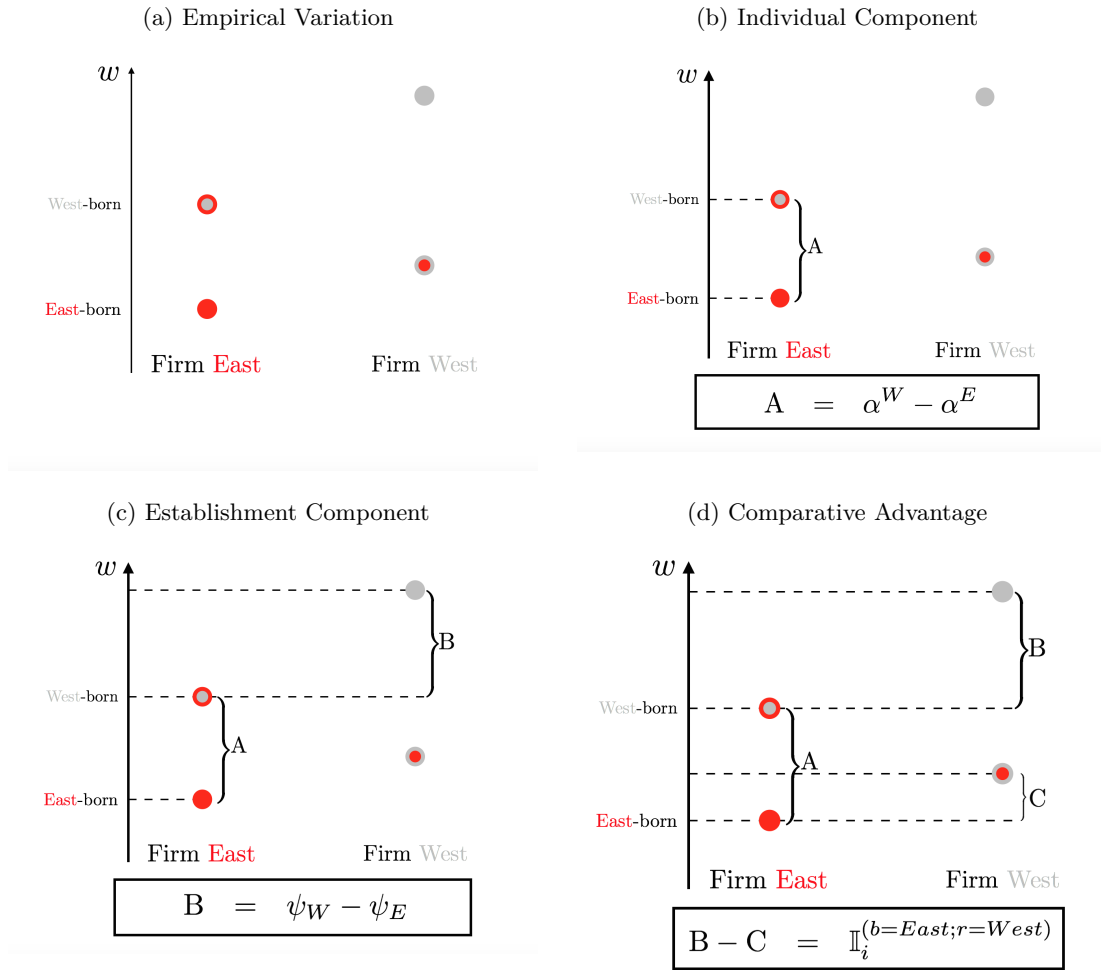
Note: The figure illustrates the wage of two workers at two establishments in East and West Germany, respectively, indexed on the x-axis. Inner coloring indicates the birth region of the worker (gray=West, red=East). Outer coloring indicates the region in which the establishment is located.

C Proofs

C.1 Equilibrium in the Goods Market

The firm's problem is

$$\hat{\pi}_j(w) = \max_{n_h, n_c, k} pn_c + P_{h,j}(pn_h)^{1-\alpha} k^\alpha - \rho_j k \tag{25}$$

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

$$n_h = \frac{\rho_j}{p} \frac{1-\alpha}{\alpha} k \tag{26}$$

and assuming that both goods are supplied in equilibrium

$$P_{h,j} = \rho_j^\alpha \alpha^{-\alpha} (1-\alpha)^{-(1-\alpha)}. \tag{27}$$

The equilibrium price of the local good is determined from consumers' demand and market clearing. The aggregate demand for the local good H_j satisfies

$$P_{h,j} H_j = (1-\eta) P_j Y_j, \tag{28}$$

where, assuming that consumers own the firms, their total income is

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

and Y_j is real GDP. On the supply side, market clearing implies $H_j = (\rho_j \frac{1-\alpha}{\alpha})^{1-\alpha} K_j$, which, using the price of the local good (27), implies

$$P_{h,j} H_j = \frac{1}{\alpha} \rho_j K_j. \tag{29}$$

Combining demand and supply yields

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

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

We can express the equilibrium condition in terms of ratios as follows. Starting from $P_j = (P_{h,j})^{1-\eta}$, we can substitute in with (27) and use the supply equation (29) to obtain

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

61

Combining this expression with the demand equation (28) gives

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

as desired.

Finally, we can plug (26) and (27) into (25) to obtain $\hat{\pi}_j(w) = pn_j(w) = p\sum_{i\in\mathbb{I}}\theta_j^i l_j^i(w)$, where capital and labor demand for the local good has been maximized out.

C.2 Proof of Proposition 1

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

$$\pi_j(p) = \max_w (p - w)\sum_{i\in\mathbb{I}}\theta_j^i l_j^i(w) \tag{30}$$

and, as shown,

$$l_j^i(w) = \frac{\mathcal{P}_j^i(w)\,\varphi_j^i\,\bar{D}^i}{q_j^i(w)} \tag{31}$$

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

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

If the function $\pi_j(p, w)$ is continuous in w for a given p, then we can take the first order condition of problem (30) and obtain

$$\frac{(p - w_j(p))\left(\sum_{i\in\mathbb{I}}\theta_j^i\frac{\partial l_j^i(w_j(p))}{\partial w}\right)}{\left(\sum_{i\in\mathbb{I}}\theta_j^i l_j^i(w_j(p))\right)} = 1. \tag{32}$$

From equation (31), we find

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

We then define the functions in terms of p,

$$s_j^i(p) \equiv q_j^i(w_j(p))$$
$$\tilde{\mathcal{P}}_j^i(p) \equiv \mathcal{P}_j^i(w_j(p))$$

so that

$$\frac{\partial s_j^i(p)}{\partial p} = \left(\frac{\partial q_j^i(w)}{\partial w}\right)\left(\frac{\partial w_j(p)}{\partial p}\right)$$

$$\frac{\partial \tilde{\mathcal{P}}_j^i(p)}{\partial p} = \left(\frac{\partial \mathcal{P}_j^i(w_j(p))}{\partial w}\right)\left(\frac{\partial w_j(p)}{\partial p}\right).$$

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

$$\frac{\partial l_j^i(w)}{\partial w} = \frac{\left(\frac{\partial w_j(p)}{\partial p}\right)^{-1}}{s_j^i(p)^2}\left(\frac{\partial \tilde{\mathcal{P}}_j^i(p)}{\partial p}s_j^i(p) - \tilde{\mathcal{P}}_j^i(p)\frac{\partial s_j^i(p)}{\partial p}\right)\varphi_j^i\bar{D}^i,$$

which can itself be substituted into (32) to find a differential equation for $w_j(p)$

$$\frac{\partial w_j(p)}{\partial p} = \frac{(p - w_j(p))\left(\sum_{i\in\mathbb{I}}\theta_j^i\frac{\frac{\partial \tilde{\mathcal{P}}_j^i(p)}{\partial p}s_j^i(p) - \tilde{\mathcal{P}}_j^i(p)\frac{\partial s_j^i(p)}{\partial p}}{s_j^i(p)^2}\varphi_j^i\bar{D}^i\right)}{\left(\sum_{i\in\mathbb{I}}\theta_j^i\frac{\tilde{\mathcal{P}}_j^i(p)}{s_j^i(p)}\varphi_j^i\bar{D}^i\right)}. \tag{33}$$

Since $w_j(p)$ is continuous at p by assumption, the differential equation (33), together with an appropriate boundary conditions, characterizes the optimal wage at p. The boundary conditions are given by

$$w_j\left(\underline{p}_j\right) = \arg\max_w \left(\underline{p}_j - w\right)\sum_{i\in\mathbb{I}}\theta_j^i l_j^i(w),$$

which has to be solved for numerically. Note that if all worker heterogeneity is shut down $- \theta_j^i = \tau_j^i = \varphi_{jx}^i = 1$ for all i, j, and x, $\delta_j^i = \delta$ and $b_j^i = b$ for all i and j, $v = 1$, $\sigma \to 0$, and $\kappa_{jx}^i = 0$, then the acceptance probability simplifies to

$$\tilde{\mathcal{P}}_j^i(p) = \frac{1}{\bar{D}_j^i}\left(\frac{\delta_j^i}{s_j^i(p)}\right).$$

In this case, we can solve for the optimal wage and separation policies from the ODEs without having to solve for the value functions, and the boundary conditions collapse to

$$w_j\left(\underline{p}_j\right) = b.$$

Next, we turn to the separation function $s_j^i(p)$. From equation (13) and using the definition of $F_j(w)$,

$$s_j^i(p) = \delta_j^i + \sum_{x\in\mathbb{J}}\varphi_{jx}^i\lambda_x\left[\frac{1}{\lambda_x}\int\mu_{jx}^i(w_j(p), w_x(z))v_x(z)\gamma_x(z)dz\right]. \tag{34}$$

Differentiating with respect to p yields the differential equation for the separation rate $s_j^i(p)$

$$\frac{\partial s_j^i(p)}{\partial p} = \sum_{x\in\mathbb{J}}\varphi_{jx}^i\int\frac{\partial\mu_{jx}^i(w_j(p), w_x(z))}{\partial w}\frac{\partial w_j(p)}{\partial p}v_x(z)\gamma_x(z)dz. \tag{35}$$

Since $w_j(p)$ is continuous at p, and furthermore $\gamma_j(p) > 0$ for all $p \in \left[\underline{p}_j, \bar{p}_j\right]$, $q_j^i(p)$ is also continuous. To fully characterize the separation rate functions, we need boundary conditions (for each (j, i)), which are given by

$$s_j^i(\bar{p}_j) \equiv \delta_j^i + \sum_{x \in \mathbb{J}} \varphi_{jx}^i \lambda_x \left[\frac{1}{\lambda_x} \int \mu_{jx}^i(w_j(\bar{p}_j), w_x(z)) v_x(z) \gamma_x(z) dz\right].$$

We have thus proved that the wage is given by

$$w_j(p) \quad = \quad w_j\left(\underline{p}_j\right) + \int_{\underline{p}_j}^{p} \frac{\partial w_j(z)}{\partial z} \gamma_j(z) dz \tag{36}$$

and the separation rate function is

$$s_j^i(p) \quad = \quad s_j^i(\bar{p}_j) + \int_{p}^{\bar{p}_j} \frac{\partial s_j^i(z)}{\partial z} \gamma_j(z) dz. \tag{37}$$

D Details on Estimation and Counterfactuals

D.1 Estimation Algorithm

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

$$\phi^* = \arg\min_{\phi \in \mathbb{F}} \mathcal{L}(\phi) \tag{38}$$

where

$$\mathcal{L}(\phi) \equiv \sum_x \left[\omega_x \left(\frac{m_x(\phi) - \hat{m}_x}{\hat{m}_x} \right)^2 \right],$$

$m_x(\phi)$ is the model-generated moment, $\hat{m}_x$ is the empirical moment, and ω_x is a weighting factor, which we describe next.

As in Jarosch (2016), Lise, Meghir, and Robin (2016), we minimize the sum of the percentage deviations between model-generated and empirical moments. Furthermore, we introduce an additional weighting factor ω_x with two purposes: i) to give equal weight to each one of the five groups of parameters that we target, shown in Table 4; ii) to prevent that some moments are given a very large weight because the associated target $\hat{m}_x$, and thus the deflator, is small. Specifically, we let $\omega_x \equiv \omega_{x,1}\omega_{x,2}$, where the two components, which we refer to as *weight* and *deflator*, address the first and second purpose just stated. Table 8 includes $\omega_{x,1}$ and $\omega_{x,2}$ for each targeted moment, respectively in columns (2) and (3).

Column (2) shows that we give higher weight to moments that are part of a group with fewer targets. For example, we target eight wage gains for movers, but only two measures of regional gaps. Therefore, we scale up the second set of moments by a factor of four, so that each group has the same weight.

Column (3) may require a more detailed explanation. As an example, consider row (4). For this moment, the target value, and thus the deflator $\hat{m}_x$, is close to zero, at 0.7%. As a result, small level deviations of the model-based moments from this target would be severely amplified: the estimation procedure would give a large weight to match the wage gain of East-born workers when moving back home. However, we are not particularly interested in that specific moment, and, in fact, would like to give a similar weight to each wage gain moment. For this reason, we use a deflator $\omega_{x,2}$, which removes the direct effect of dividing by $\hat{m}_x$ and replaces it by the percentage average wage gains for all the cross-regional moves. We use a similar idea for each one of the other targeted moments.

The minimization algorithm that we use to solve the problem (38) is a three step algorithm, adapting methods from the literature to the needs of our application. In particular, we use a mixed approach of the methods used in Jarosch (2016); Lise, Meghir, and Robin (2016) and in Moser and Engbom (2018).

First, we simulate, using Markov Chain Monte Carlo for classical estimators as introduced in Chernozhukov and Hong (2003), 100 strings of length 10,000 starting from 100 different guesses for the vector of parameters ϕ_0. We choose the initial guesses to span a large space of possible parameter vectors. For example, we consider values of the relative productivity between 0.8 and 2 (our final estimate is 1.1105), and values for the home bias between 0.5 and 1.2 (our final estimate is 0.9508). In updating the parameter vector along the MCMC simulation, we pick the variance of the shocks to target an average rejection rate of 0.7, as suggested by Gelman, Carlin, Stern, Dunson, Vehtari, and Rubin (2013). The average parameter values across the 100 strings for the

Table 8: Estimation Weights

		(1)	(2)	(3)
		Data	Weight ($\omega_{x,1}$)	Deflator ($\omega_{x,2}$)
	Average Wage Gains for Movers			
(1)	Moves from East to West (West-Born)	24.8%	1	$(24.8\%/25.1\%)^2$
(2)	Moves from East to West (East-Born)	44.7%	1	$(44.7\%/25.1\%)^2$
(3)	Moves from West to East (West-Born)	30.2%	1	$(30.2\%/25.1\%)^2$
(4)	Moves from West to East (East-Born)	0.7%	1	$(0.7\%/25.1\%)^2$
(5)	Moves Within West (West-Born)	19.6%	1	$(19.6\%/14.0\%)^2$
(6)	Moves Within West (East-Born)	15.1%	1	$(15.1\%/14.0\%)^2$
(7)	Moves Within East (West-Born)	10.1%	1	$(10.1\%/14.0\%)^2$
(8)	Moves Within East (East-Born)	11.1%	1	$(11.1\%/14.0\%)^2$
	Rates of Job-Job Mobility			
(9)	Moves from East to West (West-Born)	0.074%	1	$(0.074\%/0.039\%)^2$
(10)	Moves from East to West (East-Born)	0.021%	1	$(0.021\%/0.039\%)^2$
(11)	Moves from West to East (West-Born)	0.003%	1	$(0.003\%/0.039\%)^2$
(12)	Moves from West to East (East-Born)	0.058%	1	$(0.058\%/0.039\%)^2$
(13)	Moves Within West (West-Born)	1.291%	1	$(1.291\%/1.231\%)^2$
(14)	Moves Within West (East-Born)	1.351%	1	$(1.351\%/1.231\%)^2$
(15)	Moves Within East (West-Born)	1.174%	1	$(1.174\%/1.231\%)^2$
(16)	Moves Within East (East-Born)	1.108%	1	$(1.108\%/1.231\%)^2$
	Regional Employment Rates			
(17)	Share of West-Born working in West	97.0%	2	$(97.0\%/90.5\%)^2$
(18)	Share of East-Born working in East	83.9%	2	$(83.9\%/90.5\%)^2$
(19)	Unemployment Rate in West Germany	7.0%	2	$(7.0\%/9.5\%)^2$
(20)	Unemployment Rate in East Germany	11.9%	2	$(11.9\%/9.5\%)^2$
	Within Region Joint Distribution of Wages-Size			
(21)	Employment in 10% Largest Firms (W)	58.3%	4/3	$(58.3\%/56.4\%)^2$
(22)	Employment in 10% Largest Firms (E)	54.4%	4/3	$(54.4\%/56.4\%)^2$
(23)	Skewness of Labor Distribution (West)	0.78	4/3	$(0.78/0.74)^2$
(24)	Skewness of Labor Distribution (East)	0.70	4/3	$(0.70/0.74)^2$
(25)	Firm's Size-Wage Premium (West)	12.5%	4/3	$(12.5\%/12.0\%)^2$
(26)	Firm's Size-Wage Premium (East)	11.5%	4/3	$(11.5\%/12.0\%)^2$
	Regional Wage and GDP Gaps			
(27)	West-East Gap in Firm wage	16.9%	4	$(16.9\%/20.8\%)^2$
(28)	West-East Gap in GDP per worker	24.6%	4	$(24.6\%/20.8\%)^2$

Notes: The table shows the estimation targets and the weights and deflators used for each target in the estimation procedure.

last 1000 iterations provide a first, rough, estimate of the vector of parameters.

Second, we repeat the same MCMC procedure, but starting each string from the parameter estimates of the first step. This second MCMC run gives sensible results, which are very similar to our final estimates. Figure 13 plots, in gray, the relationship between parameter estimates and the objective function for the best 5000 parameter draws across all the Monte Carlo Chains. The larger, gray diamond is the best estimate. It is reassuring to notice that the objective function seems to be single-peaked around the minimum.

Third, and last, we compute the objective functions for 2 million parameter vectors drawn using Sobol sequences – which efficiently distribute points in a space – in a small neighborhood around the best estimate. The goal of the third step is to "zoom in" around the previous best estimate to enhance the precision of our estimate. The black diamonds show our final best estimate. In fact, as can be seen again in Figure 13, this last step marginally changes the parameter estimates and improves slightly the fit of the model.

D.2   Robustness to Different Values of Unemployment

In this section, we explore the robustness of our results to different values of unemployment. In the benchmark calibration, we used a value of $b = 0.60\underline{p}$, where $\underline{p}$ is the productivity level of the lowest productivity firm. We here re-estimate the 13 model-estimated parameters, keeping all other *calibrated* parameters constant, but using two alternative values for unemployment: $b_{low} = 0.40\underline{p}$ and $b_{high} = 0.80\underline{p}$. The resulting estimated parameters are shown in Table 9. As expected, changing the unemployment values impacts some of the estimated parameters. In particular, when the unemployment value is higher (column 3), the model requires a higher relative search intensity of unemployed workers (ν) to match the level of unemployment. Otherwise, the model would generate too much unemployment since when b is high, the unemployed workers reject a higher share of offers.[60]

Nonetheless, the estimated parameters of interest are broadly consistent with our benchmark estimation. In particular, the values of the taste bias and migration costs are only slightly affected. Moreover, we notice that the migration friction and the taste bias move in the same direction, thus implying that the main message of our counterfactual exercises is robust across the different calibrations of b. Finally, we notice that the value of the minimized objective function is slightly lower, hence the fit of the model slightly better, with the benchmark value of b.

To more throughly investigate the sensitivity of our estimates to the value of b, in Figure 14 we plot, for a few key parameters of interest, the histograms of the estimates that provide the smallest 500 values for the objective function, as computed during the last step of the minimization algorithm. We should interpret the figure as providing the distributions around the estimated point estimates, which give a rough notion of the standard errors of the estimated parameters. We notice that, as already emphasized, the relative search of unemployed workers is higher for b_{high}. However, and most importantly, the distributions for the four key parameters of interest that govern taste bias and migration costs are very similar across the two values of unemployment.

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[60]The opposite is true when the unemployment value is lower than the benchmark.

Figure 13: Estimated Coefficients and Objective Function
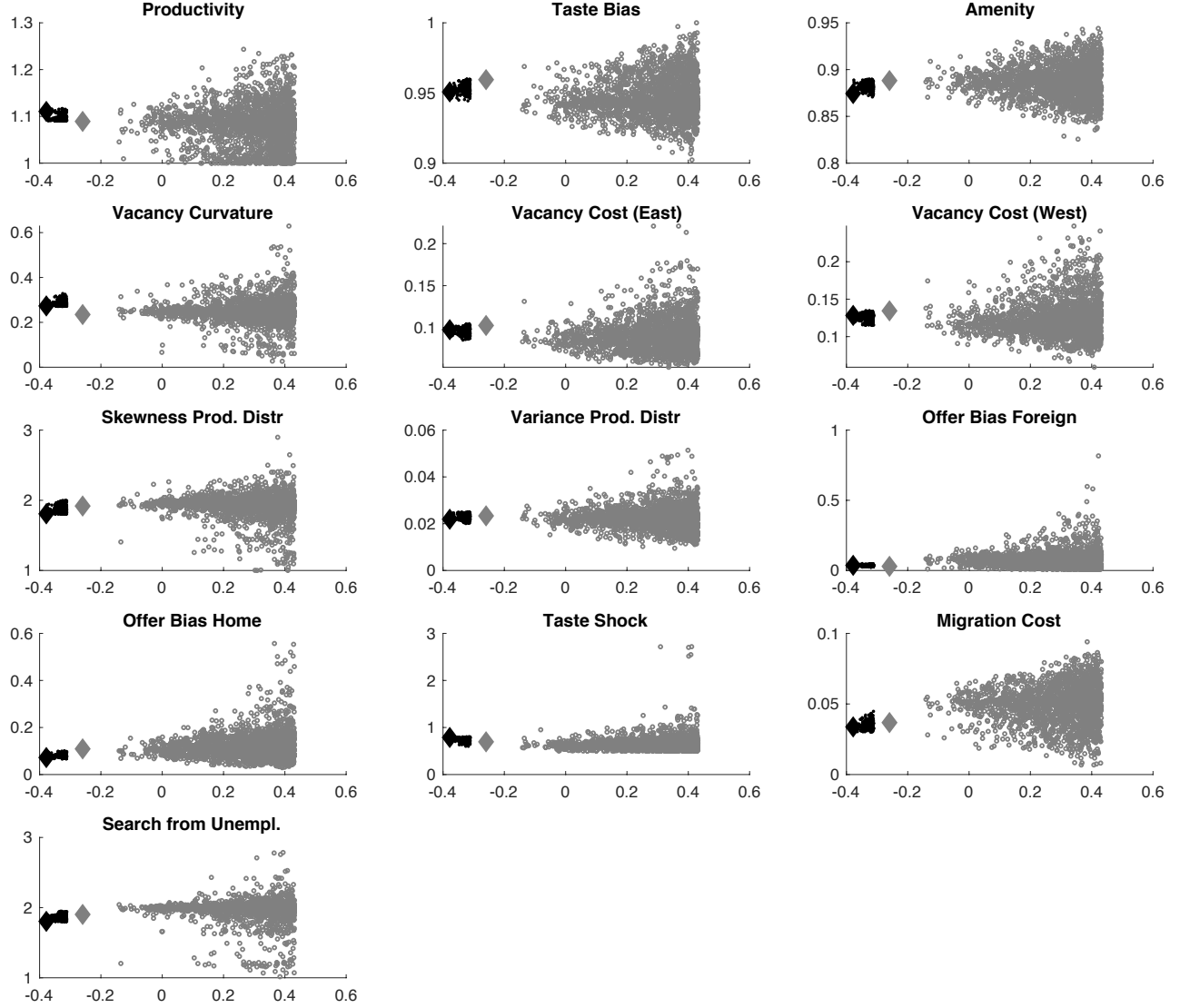
Notes: we plot, for each of the 13 estimated parameters, the parameter draw as a function of the corresponding objective function for the best parameter draws. The gray dots plot the best 5,000 parameter draws along all the 100 chains simulated at step two of our minimization algorithm. The black dots plot the best 500 parameter draws among the 2 million draws for which we computed the objective function in the last step of the algorithm. The gray diamond is the best estimate from step two. The black diamond is our final best estimate, which we report in the main text.

Table 9: Estimated Parameters with Alternative Unemployment Values

		Benchmark	Low b	High b
	Estimated Remaining Home Bias and Mobility Frictions			
(11)	$1 - \tau_h$: Preference for Home-Region	4.92%	5.73%	3.71%
(12)	κ: Mobility Cost to Cross-Regions	3.38%	4.46%	2.81%
(13)	φ_{fh}: Offer Bias from Home Region	7.21%	7.49%	8.26%
(14)	φ_{hf}: Offer Bias from Foreign Region	3.66%	3.88%	2.32%
	Estimated Productivity and Amenity Differences			
(15)	Z: Productivity Gain of West-Firms	11.05%	7.76%	7.85%
(16)	$1 - \tau_W$: Preference for West Germany	-12.56%	-12.00%	-10.31%
(17)	γ_1: Variance of Firm Productivity	0.022	0.030	0.025
(18)	γ_2: Skewness of Firm Productivity	1.81	1.84	1.89
	Estimated Labor Market Frictions			
(19)	$\chi_{0,W}$: Level of Vacancy Cost (West)	0.128	0.123	0.117
(20)	$\chi_{0,E}$: Level of Vacancy Cost (East)	0.098	0.087	0.091
(21)	χ_1: Curvature of Vacancy Cost	3.66	0.022	0.022
(22)	σ: Variance of Taste Shocks	0.79	0.71	0.78
(23)	ν: Relative Search Intensity of Unemployed	1.80	1.75	1.97
	Overall Model Fit			
(24)	Objective Function	0.6852	0.7848	0.7851

 Notes: The table presents the estimated parameters in the benchmark case and compares them with the estimates for two alternative scenarios with either a lower or a higher value of unemployment benefits.

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Figure 14: Histogram of Parameters for Best 500 Estimates
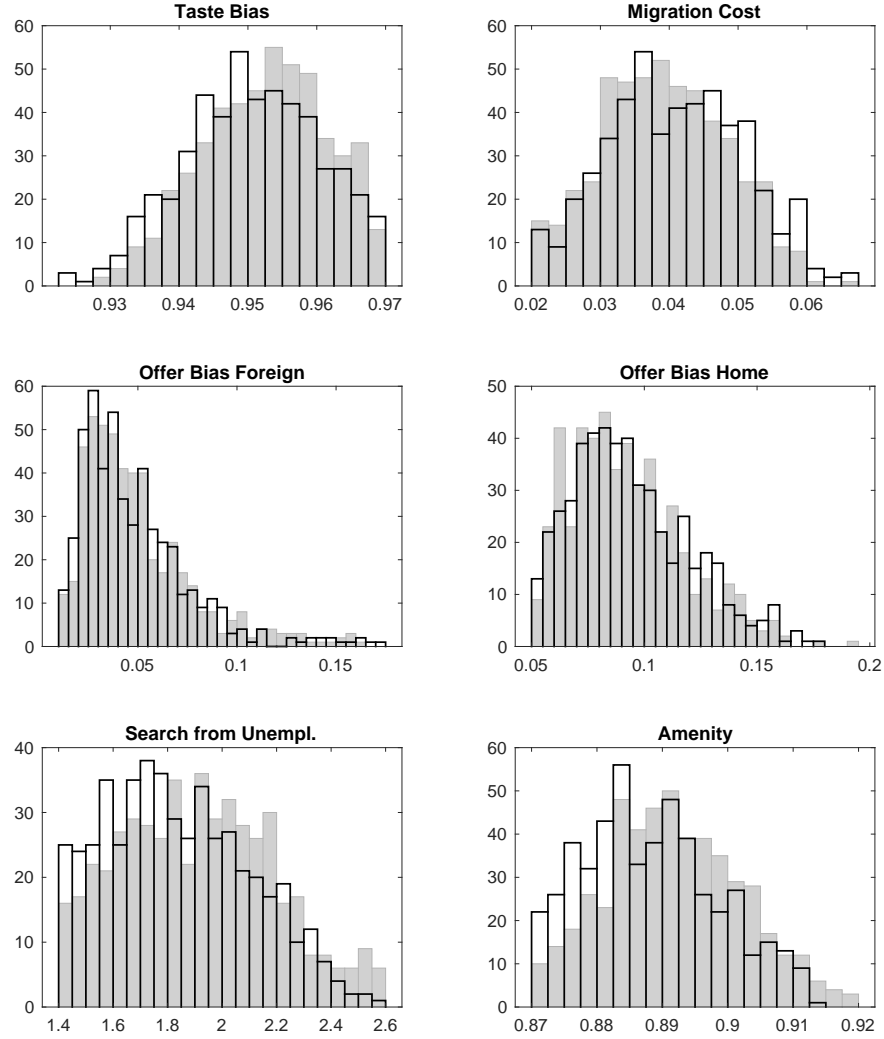
Notes: We plot in each panel the distributions of the parameter values that achieve the smallest 500 values for the objective function computed during the last step of the minimization algorithm. In gray, we plot the distributions for the estimates when $b = b_{high}$. In white, we plot the ones for the case when $b = b_{low}$.

D.3 Size of the Subsidies

We present here the size of the hiring subsidies. First, the hiring subsidy ϖ is calibrated to be the same as the cost of subsidizing migration moves, at that equilibrium outcome:

$$
\underbrace{\kappa \sum_{i \in \mathbb{I}} \left[\sum_{j \neq x} \varphi_{jx}^i \hat{\lambda}_x \int \left(\int \hat{\mu}_{jx}^i (w, w') \, d\hat{F}_x (w') \right) d\hat{G}_j^i (w) \right]}_{\text{Cost to subsidize job-job migration moves}}
$$

$$
\underbrace{+\kappa \sum_{i \in \mathbb{I}} \left[\sum_{j \neq x} \varphi_{jx}^i \hat{\lambda}_x \left(\int \hat{\mu}_{jx}^i (b, w') \, d\hat{F}_x (w') \right) \nu u_j^i \right]}_{\text{Cost to subsidize unemp-job migration moves}} \quad = \quad \underbrace{\varpi \sum_{j \in \mathbb{J}} \int c_j \left(v_j (z) \right) \gamma (z) \, dz.}_{\text{Cost of the hiring subsidy}}
$$

Here, hats denote equilibrium outcomes for the version of the model with migration subsidies.

Second, the hiring subsidy ρ is calibrated such that the total number of posted vacancies is the same as the ones posted by the equivalent migration subsidy:

$$
\underbrace{\sum_{i \in \mathbb{I}} \sum_{j \in \mathbb{J}} \sum_{x \in \mathbb{J}} \int \left(1 - \varphi_{jx}^i \right) \left(e_x^i + u_x^i \right) v_j (p) \gamma_j (p) \, dp}_{\text{Mass of vacancies to required to eliminate offer bias}} \quad = \quad \underbrace{\rho \sum_{i \in \mathbb{I}} \sum_{j \in \mathbb{J}} \varphi_j^i \bar{D}^i \lambda_j}_{\text{Mass of additional vacancies in hiring subsidy}} .
$$

E Additional Figures

Figure 15: Price Level and Unemployment

(a) Price Level, 2007   (b) Average Unemployment, 2009-2014
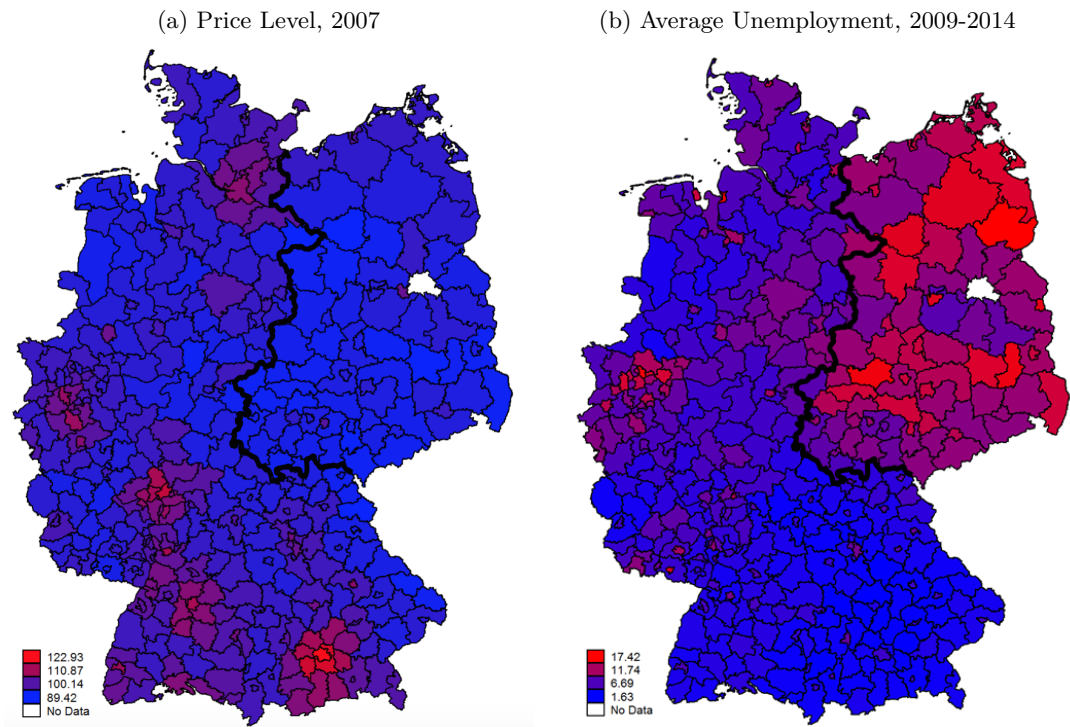
Sources: BBSR, Bundesagentur für Arbeit. Notes: The left figure plots the price level in 2007 for each county, in euros valued in Bonn, the former capital of West Germany, from the BBSR. The right figure shows the unemployment rate, calculated as all unemployed workers divided by (unemployed + civilian dependent workers).

Figure 16: Cumulative Distribution Functions of Real Wages in East and West
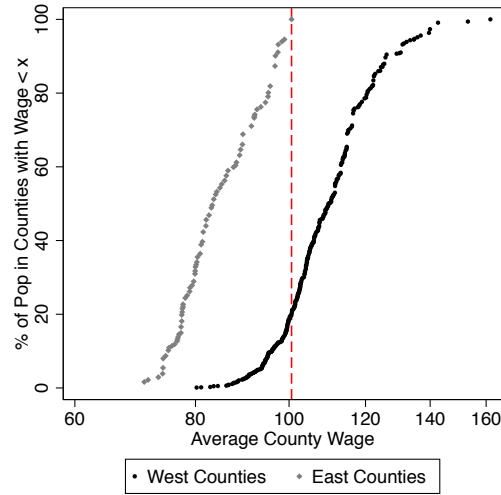
Source: BHP. Note: The figure shows the CDF of real wages across East and West German counties. Each dot is a county, where the steepness of the CDF is determined by the share of each region's population captured by the county. The red-dashed line shows the average real wage of the highest-paying county in East Germany.

Figure 17: Population and Real Wage by Education

(a) Share of Highly-Skilled Workers by County
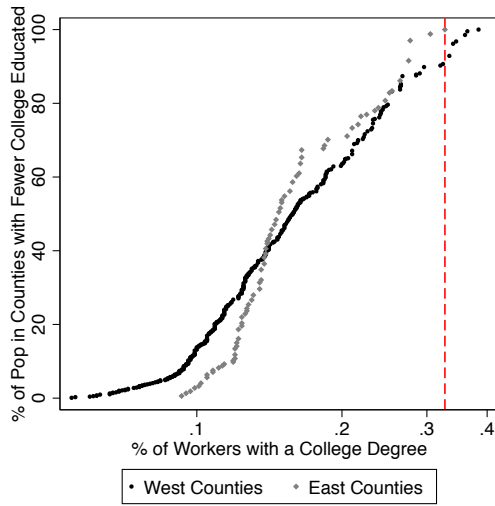
(b) Real Wage by Highly-Skilled Share Across Counties

Source: BHP. Note: The left figure shows the CDF of the share of workers with a college degree in each county, where this share is calculated as the number of full-time workers with a value of 5 or 6 in the B2 code divided by all full-time workers. Each dot is a county, where the steepness of the CDF is determined by the share of each region's population captured by the next county. The red-dashed line shows the maximum of the average share of high-skilled in East Germany. The right figure plots the share of college educated in each county against the average real wage of the county. The size of each dot is determined by the population in each county.

Figure 18: Real Wage and Population by Industry

(a) Real Wage Gap by Industry   (b) Share of College-Educated by Industry in East vs. West
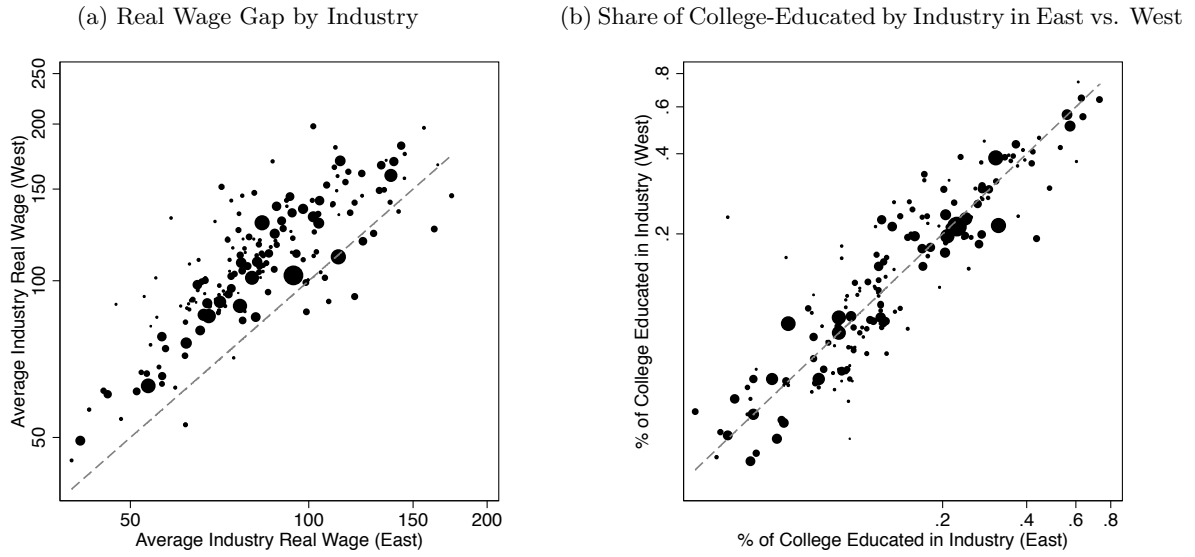
Source: BHP. Note: The left figure plots the average real wage in East Germany against the average real wage in West Germany at the industry-level. Each industry is a 3-digit WZ93 code, using the concordance by Eberle, Jacobebbinghaus, Ludsteck, and Witter (2011). The right figure plots the share of college-educated workers in East Germany against the share of college-educated in West Germany at the industry-level, where the share of college-educated is calculated as the number of full-time workers with a value of 5 or 6 in the B2 code divided by all full-time workers. The size of each dot is determined by the number of full-time workers in each industry.

Figure 19: Real Wage by Share of Males Across Counties
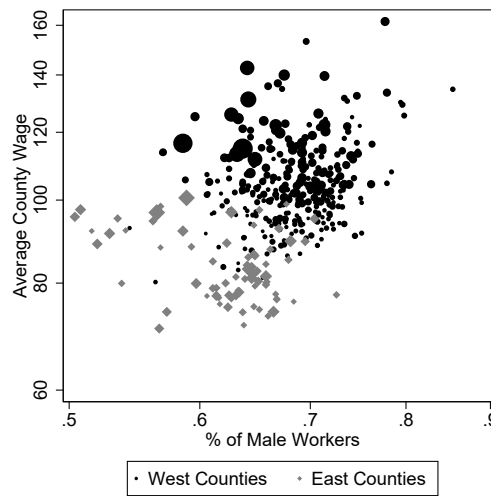
Source: BHP. Notes: The figure plots the share of full-time male workers in each county against the average real wage of the county. The size of each dot is determined by the population in each county.

Figure 20: East-West Mobility over Time

(a) Net Flows Across Regions by Home Region
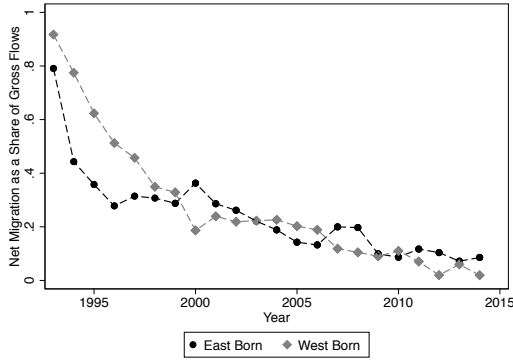
(b) Stock of Workers away from Home Region
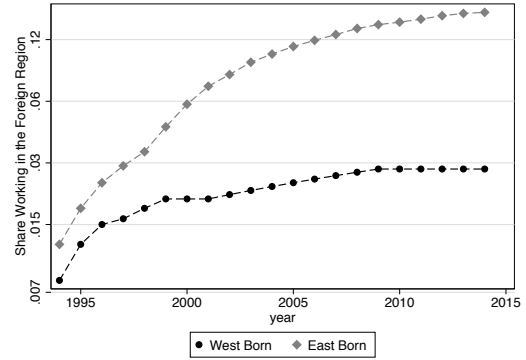
Source: LIAB. Notes: The left figure shows the number of workers moving out of their home region minus the number of workers moving back in a given year, divided by the total number of workers moving across regions. The right figure plots the share of workers by home region currently working in the other region. Each worker is counted once each year, regardless of the number of spells.

Figure 21: Origin FE
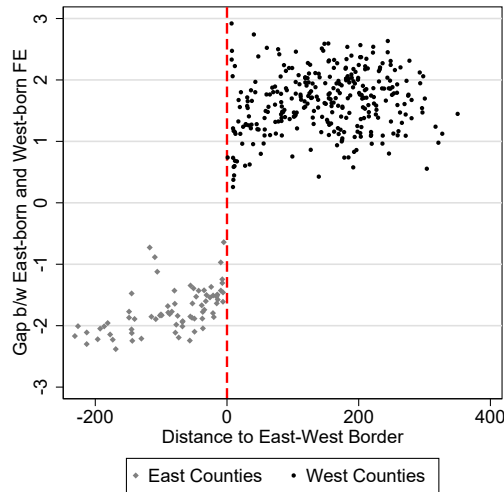
Source: LIAB and authors' calculations. Notes: The figure plots the difference between the origin fixed effects for East- and West-born workers obtained from regression (3), plotted as a function of the county distance to the East-West border. A negative gap implies that East-born workers are less likely to move out of a given county, i.e., they have a smaller origin fixed effect than West-born workers for that county.

Figure 22: Firm Wage and Size Distributions in East and West
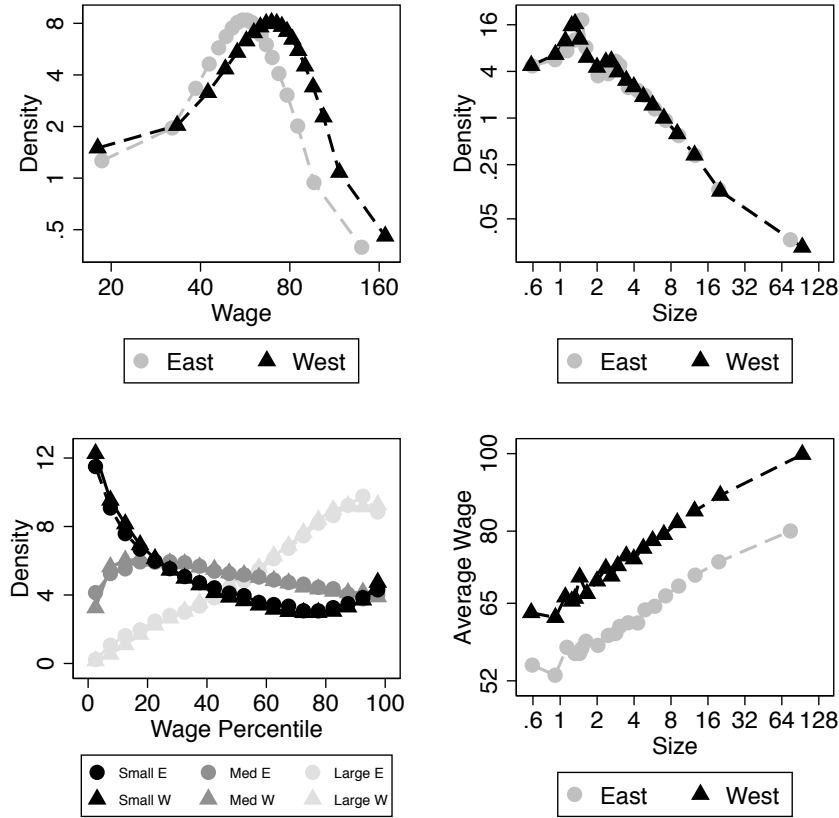
Source: BHP. Notes: The figure plots the joint distribution of firm size and wage in East and in West Germany. Both size and wage are residualized to account for variation that is not in our model, by regressing the raw log size and log wage on 3-digit industry dummies and time dummies, for East and West Germany separately. We then generate the residualized wage as the residuals from this regression plus the mean of the wage in the given region. We perform a similar exercise for size. The top left panel shows the resulting wage distributions in East and in West Germany. The top right panel presents the size distributions. The bottom left panel presents cuts of the joint distribution by plotting the density of the wage distribution at different percentiles of wages, for "small" firms (all firms up to the 15th percentile of the size distribution), "medium" firms (all firms between the 45th and 55th percentile), and "large" firms (above the 85th percentile). The bottom right panel shows the firm size plotted against the wage.

Figure 23: Probability of Unemployment for Cross-Region Moves

(a) East to West Move　　　　　　　　(b) West to East Move
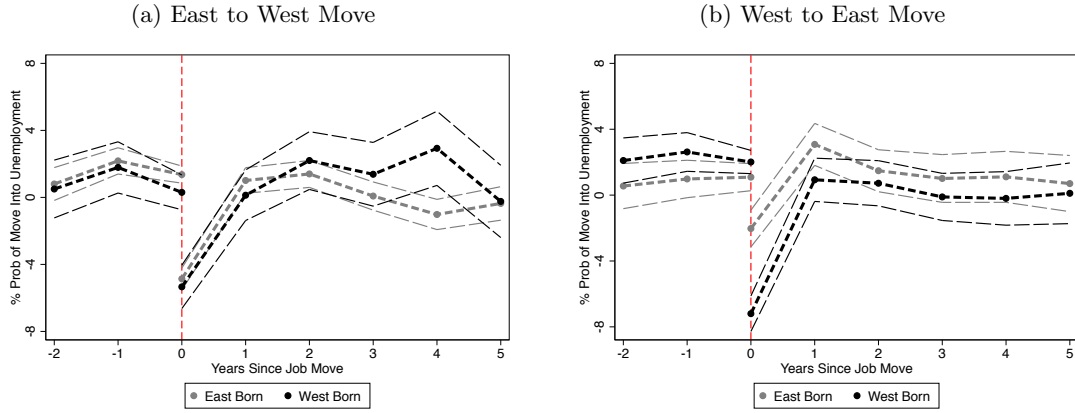
Source: LIAB and authors' calculations. Notes: The figures present the probability that a worker moving between regions in year 0 becomes unemployed in the years before and after the move. We calculate these probabilities by running regression (2) with the probability of becoming unemployed as the left-hand side variable. We obtain the estimated coefficients $\beta_{EW_m\tau}^{East}$ and $\beta_{EW_m\tau}^{West}$ (left panel) and $\beta_{WE_m\tau}^{East}$ and $\beta_{WE_m\tau}^{West}$ (right panel), and normalize them with respect to the probability of becoming unemployed in the year of the move.

F   Additional Tables

Table 10: Effect of Region on Real Wage (Unweighted Estimates)

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

Notes: $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the establishment level.

Table 11: Imputed Home Region in the LIAB vs. Birth Region in the SOEP

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

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

Table 12: Wage Gaps by Imputed Home Region versus Birth Region in the SOEP

w_{it}	Old SOEP Sample				New SOEP Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{I}_i^{East}$	$-.3495^{***}$	$-.4054^{***}$			$-.1586^{***}$	$-.1485^{***}$		
	(.0214)	(.0198)			(.0319)	(.0302)		
$\mathbb{I}_i^{East,true}$			$-.3376^{***}$	$-.4041^{***}$			$-.1221^{***}$	$-.1173^{***}$
			(.0209)	(.0193)			(.0313)	(.0292)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Age/edu/male	−	Y	−	Y	−	Y	−	Y
Observations	$16,000$	$15,969$	$16,000$	$15,969$	$3,200$	$2,803$	$3,200$	$2,803$

Notes: $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the individual level. $\mathbb{I}_i^{East}$ is the imputed home region dummy using the same procedure as in the LIAB. $\mathbb{I}_i^{East,true}$ is a dummy for a worker's birth region (Old SOEP sample) or region of earliest non-tertiary schooling (Young SOEP sample) as read off from the SOEP survey. See the Data section for the definition of the two SOEP samples.

Table 13: Wage Gains Robustness

Δw_{it}	(1)	(2)	(3)	(4)	(5)	(6)
			Local Projection Coefficients, $t=0$			
	Baseline	Month gap	≤ 2 mths	≥ 150km	≥ 100km	Any move
			Migration			
$d_{it}^{EW,m}(\mathbb{I}_i^{East}=0)$	**.2483*****	**.0829*****	**.1110*****	**.1466*****	**.1482*****	**.1560*****
	(.0373)	(.0258)	(.0204)	(.0137)	(.0135)	(.0120)
$d_{it}^{WE,m}(\mathbb{I}_i^{East}=0)$	**.3020*****	$-.0438$	$-.0189$	**.1712*****	**.1627*****	**.1526*****
	(.0327)	(.0294)	(.0233)	(.0131)	(.0126)	(.0113)
$d_{it}^{EW,m}(\mathbb{I}_i^{East}=1)$	**.4473*****	**.1517*****	**.1296*****	**.2066*****	**.2019*****	**.2058*****
	(.0186)	(.0141)	(.0099)	(.0066)	(.0063)	(.0056)
$d_{it}^{WE,m}(\mathbb{I}_i^{East}=1)$	.0073	$-.0753$***	$-.0429$***	**.0390*****	**.0415*****	**.0448*****
	(.0293)	(.0181)	(.0132)	(.0129)	(.0126)	(.0122)
			Commuting			
$d_{it}^{EW,c}(\mathbb{I}_i^{East}=0)$	**.1029*****	**.0549*****	**.0639*****	**.1427*****	**.1415*****	**.1366*****
	(.0137)	(.0108)	(.0088)	(.0096)	(.0097)	(.0103)
$d_{it}^{WE,c}(\mathbb{I}_i^{East}=0)$	**.1111*****	.0102	**.0246****	**.0765*****	**.0748*****	**.0655*****
	(.0140)	(.0097)	(.0103)	(.0120)	(.0125)	(.0148)
$d_{it}^{EW,c}(\mathbb{I}_i^{East}=1)$	**.1812*****	**.0667*****	**.0806*****	**.1975*****	**.2103*****	**.1783*****
	(.0095)	(.0056)	(.0055)	(.0091)	(.0103)	(.0190)
$d_{it}^{WE,c}(\mathbb{I}_i^{East}=1)$	**.0682*****	$-.0044$	**.0362*****	**.0872*****	**.0866*****	**.0861*****
	(.0095)	(.0057)	(.0056)	(.0058)	(.0058)	(.0058)
Year FE	Y	Y	Y	Y	Y	Y
Indiv FE	Y	Y	Y	Y	Y	Y
Mobility controls	Y	Y	Y	Y	Y	Y
Age controls	Y	Y	Y	Y	Y	Y
Observations	$8,969,682$	$6,122,208$	$5,520,086$	$6,122,208$	$6,122,208$	$6,122,208$

Notes: $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the individual level. Column (1) presents the benchmark regression for $\tau = 0$. Column (2) adds to the benchmark regression a control for the number of months between job spells. Column (3) drops all job switches where more than two months elapse between jobs. Column (4) classifies any job move exceeding a distance over 150km as migration, and Column (5) classifies moves over 100km as migration. Column (6) classifies any job switch out of the current region to the other region as migration.

Table 14: Wage Gains for Sub-Groups (Benchmark Specification), $t = 0$

Δw_{it}	Males	Females	College	No college	Young	Middle	Older	Non-German
				Migration				
$d_{it}^{EW,m}(\mathbb{1}_i^{East}=0)$	.1516***	.2429***	.2281***	.2026***	.2300***	.1569***	.1182***	.1847***
	(.0258)	(.0361)	(.0286)	(.0296)	(.0291)	(.0381)	(.0458)	(.0665)
$d_{it}^{WE,m}(\mathbb{1}_i^{East}=0)$	.1616***	.2750***	.4793***	.0573*	.3183***	.0729	−.0955*	.2336***
	(.0317)	(.0433)	(.0432)	(.0298)	(.0337)	(.0449)	(.0555)	(.0834)
$d_{it}^{EW,m}(\mathbb{1}_i^{East}=1)$	.3041***	.4608***	.5890***	.3186***	.4202***	.1953***	.1044***	.1800***
	(.0147)	(.0240)	(.0307)	(.0137)	(.0152)	(.0265)	(.0294)	(.0409)
$d_{it}^{WE,m}(\mathbb{1}_i^{East}=1)$	.0101	.0318	.1652***	.0106	.0407**	.0120	.0292	.2675
	(.0180)	(.0237)	(.0306)	(.0161)	(.0160)	(.0402)	(.0576)	(.1692)
DiD Migr	−.304	−.461	−.675	−.163	−.468	−.099	.139	.039
				Commuting				
$d_{it}^{EW,c}(\mathbb{1}_i^{East}=0)$	.1110***	.1939***	.2594***	.1305***	.1891***	.1232***	.0718***	.1453***
	(.0091)	(.0230)	(.0190)	(.0096)	(.0136)	(.0160)	(.0149)	(.0343)
$d_{it}^{WE,c}(\mathbb{1}_i^{East}=0)$	.0900***	.1554***	.2660***	.0945***	.2068***	.0447***	.0320*	.1638***
	(.0102)	(.0264)	(.0239)	(.0106)	(.0155)	(.0184)	(.0165)	(.0402)
$d_{it}^{EW,c}(\mathbb{1}_i^{East}=1)$	.1321***	.2070***	.3051***	.1525***	.2069***	.1166***	.0719***	.0810*
	(.0063)	(.0130)	(.0177)	(.0060)	(.0079)	(.0123)	(.0099)	(.0462)
$d_{it}^{WE,c}(\mathbb{1}_i^{East}=1)$	.0601***	.1441***	.2165***	.0829***	.1183***	.0799***	.0339***	.0580
	(.0064)	(.0123)	(.0157)	(.0061)	(.0075)	(.0134)	(.0111)	(.0550)
DiD Comm	−.051	−.024	−.095	−.034	−.106	.042	.002	−.042
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Indiv. controls	Y	Y	Y	Y	Y	Y	Y	Y
Mobility	Y	Y	Y	Y	Y	Y	Y	Y
Age controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	4,366,963	1,745,245	1,026,916	5,095,292	2,399,693	1,573,734	2,148,781	339,387

Notes: *, **, and * * * indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the individual level. Workers with college are workers with a value of 5 or 6 in the B2 code. Young workers were born from 1975 onwards. Middle-aged workers were born 1965-1974. Older workers were born before 1965. Non-Germans are those workers that are recorded as having non-German nationality in the LIAB data. The rows "DiD Migr" and "DiD Comm" verify the presence of home bias, and are calculated as $(d_{it}^{EW,m}(\mathbb{1}_i^{East}=0) - d_{it}^{WE,m}(\mathbb{1}_i^{East}=0)) - (d_{it}^{EW,m}(\mathbb{1}_i^{East}=1) - d_{it}^{WE,m}(\mathbb{1}_i^{East}=1))$ for migrants, and analogously for commuters. A negative value indicates that the difference in the wage gain moving out of the East compared to returning is larger for East Germans than for West Germans, i.e., home bias.

Table 15: Summary Statistics on Mobility

		(1)	(2)	(3)	(4)
		Movers before 1996		Movers after 2004	
		Home: West	Home: East	Home: West	Home: East
(1)	Returned movers	55.2%	70.2%	48.9%	44.3%
(2)	Mean years away	6.20	4.51	2.03	2.16
(3)	Number cross-border moves				
(4)	...1	42.8%	23.4%	37.4%	46.5%
(5)	...2 − 3	35.5%	47.7%	53.3%	45.0%
(6)	...4 − 6	13.7%	22.1%	8.0%	7.8%
(7)	...7+	8.0%	6.8%	1.3%	0.8%

Notes: The table presents statistics on workers in our core sample (2009-2014) that have moved out of their home region, based on the period of their first move out: workers that moved out before 1996 (Columns (1)-(2)) and workers that moved out after 2004 (Columns (3)-(4)). Row (1) presents the share of workers, among thse movers, that have since returned to a job in their home region. Row (2) shows the mean number of years away in the other region. Rows (4)-(7) show the share of workers with a given number of cross-border moves.

Table 16: Gravity Regression Coefficients - Baseline Specification

	$\hat{\beta}$	s.e.		$\hat{\beta}$	s.e.
ϕ_{50-99}	-1.7842^{***}	(.0188)	$\phi_{350-399}$	-3.0492^{***}	(.0191)
$\phi_{100-149}$	-2.5107^{***}	(.0185)	ϕ_{400+}	-3.1481^{***}	(.0188)
$\phi_{150-199}$	-2.7716^{***}	(.0184)	ψ_{1-99}	-0.0165^{***}	(.0105)
$\phi_{200-249}$	-2.8899^{***}	(.0185)	$\psi_{100-149}$	0.0367^{***}	(.0146)
$\phi_{250-299}$	-2.9491^{***}	(.0187)	$\psi_{150-199}$	0.0689^{***}	(.0152)
$\phi_{300-349}$	-2.9964^{***}	(.0189)	$\psi_{200-249}$	0.1326^{***}	(.0151)
	Observations	$94,203$			

Notes: $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively.

Table 17: Gravity Equation for Sub-Groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline	Males	Females	College	No college	Young	Middle	Older	Non-German	No unemp
$\mathbb{1}^{East}$	.1564***	.1642***	−.0475***	.2435***	.1236***	−.0249***	.3441***	.0704***	1.0737***	.1683***
	(.0071)	(.0076)	(.0115)	(.0116)	(.0076)	(.0089)	(.0105)	(.0110)	(.0229)	(.0189)
ϕ_{50-100}	−1.8128***	−1.7278***	−1.5692***	−1.0707***	−1.8340***	−1.6926***	−1.4936***	−1.4891***	−1.2353***	−1.7224***
	(.0187)	(.0189)	(.0200)	(.0194)	(.0190)	(.0187)	(.0199)	(.0214)	(.0251)	(.0189)
$\phi_{101-150}$	−2.5488***	−2.4143***	−2.1287***	−1.4762***	−2.5640***	−2.3488***	−2.0042***	−1.9746***	−1.5205***	−2.3939***
	(.0184)	(.0187)	(.0204)	(.0198)	(.0188)	(.0187)	(.0203)	(.0217)	(.0268)	(.0188)
$\phi_{151-200}$	−2.8004***	−2.6302***	−2.2834***	−1.5808***	−2.7941***	−2.5499***	−2.1195***	−2.1090***	−1.5927***	−2.6061***
	(.0184)	(.0187)	(.0207)	(.0201)	(.0189)	(.0187)	(.0205)	(.0221)	(.0278)	(.0188)
$\phi_{201-250}$	−2.9121***	−2.7286***	−2.3417***	−1.6314***	−2.9032***	−2.6380***	−2.1516***	−2.1401***	−1.6570***	−2.6961***
	(.0185)	(.0188)	(.0210)	(.0205)	(.0190)	(.0190)	(.0205)	(.0220)	(.0297)	(.0190)
$\phi_{251-300}$	−2.9669***	−2.7754***	−2.3650***	−1.6535***	−2.9452***	−2.6725***	−2.2042***	−2.1523***	−1.6502***	−2.7442***
	(.0187)	(.0190)	(.0213)	(.0211)	(.0191)	(.0192)	(.0209)	(.0224)	(.0297)	(.0192)
$\phi_{301-350}$	−3.0074***	−2.8111***	−2.3672***	−1.6701***	−2.9846***	−2.7112***	−2.1915***	−2.1443***	−1.6812***	−2.7781***
	(.0189)	(.0193)	(.0219)	(.0219)	(.0194)	(.0194)	(.0216)	(.0232)	(.0299)	(.0195)
$\phi_{351-400}$	−3.0536***	−2.8535***	−2.4029***	−1.7064***	−3.0296***	−2.7498***	−2.2273***	−2.1956***	−1.7018***	−2.8225***
	(.0191)	(.0195)	(.0224)	(.0223)	(.0197)	(.0198)	(.0221)	(.0233)	(.0316)	(.0198)
ϕ_{401+}	−3.1369***	−2.9287***	−2.4343***	−1.7564***	−3.1008***	−2.8126***	−2.2798***	−2.1936***	−1.7359***	−2.8904***
	(.0187)	(.0191)	(.0213)	(.0211)	(.0191)	(.0192)	(.0210)	(.0225)	(.0292)	(.0192)
$\mathbb{1}(R(o)\neq R(d))$	.0265***	.0390***	.0115	−.0397***	.0478***	.0815***	.077	−.0130	.2314***	.0281***
	(.0081)	(.0085)	(.0118)	(.0124)	(.0085)	(.0094)	(.0111)	(.0117)	(.0240)	(.0090)
$\mathbb{1}(R(o)=b)$	−1.6285***	−1.6354***	−1.8305***	−1.6465***	−1.6733***	−1.7593***	−1.6779***	−1.8614***	−1.6417***	−1.6696***
	(.0065)	(.0069)	(.0105)	(.0105)	(.0070)	(.0080)	(.0095)	(.0103)	(.0199)	(.0073)
$\mathbb{1}(R(d)=b)$	0.6005***	.5579***	.4525***	.3599***	.5745***	.5785***	.4084***	.4022***	.2733***	.5526***
	(.0065)	(.0070)	(.0100)	(.0107)	(.0069)	(.0078)	(.0097)	(.0102)	(.0216)	(.0074)
Observations	94,203	81,211	42,652	33,875	84,441	69,415	40,835	38,016	16,166	75,823

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the individual level. Row (1) presents the baseline regression with all workers. Rows (2)-(3) distinguish workers by gender. Rows (4)-(5) distinguish workers by education: workers with college are workers with a value of 5 or 6 in the B2 code. Rows (6)-(8) distinguish workers by age: young workers were born from 1975 onwards. Middle-aged workers were born 1965-1974. Older workers were born before 1965. Row (9) shows the results for non-Germans, which are those individuals with non-German nationality in the LIAB. Row (10) excludes all job transitions via unemployment.

Table 18: Migration Regressions - Benchmark, Additional Coefficients

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Δw_{it}					Δ Complex	Δ Est. FE
(1)	$\mathbb{I}_i^{East}$	**.0027*****	**−.0042*****	**−.0042*****			**−.0060*****	**−.0016*****
		(.0006)	(.0006)	(.0006)			.0005	.0000
(2)	$\mathbb{I}_{j,East}$	**−.0031*****	−.0009	−.0012	**.0020****	.0073	**−.0040****	**−.0003****
		(.0008)	(.0008)	(.0008)	(.0009)	(.0048)	(.0009)	(.0000)
(3)	$\mathbb{I}_i^{East}\mathbb{I}_{j,East}$	**−.0021****	**.0050*****	**.0056*****	.0014	**.0179*****	**.0116*****	**.0014*****
		(.0010)	(.0011)	(.0011)	(.0009)	(.0055)	(.0010)	(.0000)
	Within Region							
(4)	$d_{it}^{EE,W}$	**.0591*****	**.0592*****	**.1258*****	**.1280*****	**.1041*****	**.0201*****	**.0434*****
		(.0043)	(.0043)	(.0044)	(.0052)	(.0060)	(.0061)	(.0022)
(5)	$d_{it}^{WW,W}$	**.1193*****	**.1108*****	**.1707*****	**.1731*****	**.1581*****	**.0490*****	**.0491*****
		(.0008)	(.0008)	(.0015)	(.0016)	(.0018)	(.0017)	(.0008)
(6)	$d_{it}^{EE,E}$	**.0862*****	**.0786*****	**.1337*****	**.1362*****	**.1200*****	**.0229*****	**.0459*****
		(.0012)	(.0012)	(.0016)	(.0019)	(.0020)	(.0021)	(.0009)
(7)	$d_{it}^{WW,E}$	**.0978*****	**.0944*****	**.1563*****	**.1598*****	**.1407*****	**.0400*****	**−.0693*****
		(.0026)	(.0026)	(.0029)	(.0031)	(.0037)	(.0037)	(.0088)
	Commuting							
(8)	$d_{it}^{EW,W,c}$	**.0894*****	**.0853*****	**.1379*****	**.1454*****	**.1406*****	−.0091	**.0816*****
		(.0084)	(.0084)	(.0086)	(.0097)	(.0127)	(.0096)	(.0044)
(9)	$d_{it}^{WE,W,c}$	**.0705*****	**.0641*****	**.1127*****	**.1175*****	**.1142*****	**.0515*****	.0044
		(.0096)	(.0096)	(.0098)	(.0111)	(.0127)	(.0104)	(.0047)
(10)	$d_{it}^{EW,E,c}$	**.1285*****	**.1252*****	**.1580*****	**.1622*****	**.1610*****	**.0291*****	**.1006*****
		(.0054)	(.0054)	(.0057)	(.0067)	(.0072)	(.0067)	(.0031)
(11)	$d_{it}^{WE,E,c}$	**.0622*****	**.0486*****	**.0871*****	**.0931*****	**.0856*****	**−.0156*****	**−.0180*****
		(.0053)	(.0053)	(.0057)	(.0067)	(.0072)	(.0068)	(.0031)
	Observations	6,122,208	6,122,208	6,122,208	5,418,760	6,122,208	5,595,187	5,796,165

Notes: ∗, ∗∗, and ∗ ∗ ∗ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the individual level.