Workers' Home Bias and Spatial Wage Gaps*

Lessons from the Enduring Divide between East and West Germany

Sebastian Heise[†]
Federal Reserve Bank of New York

Tommaso Porzio[‡]
University of California, San Diego and CEPR

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Abstract

Even within dynamic and integrated labor markets, real wage differences across regions often persist for decades. Germany is an example: more than 25 years after the East-West reunification, firms in the East are still paying 17% lower real wage per efficiency unit of labor. We use detailed microdata, interpreted through a new model of worker reallocation across regions and firms, to show that workers' attachment towards their home region, or home bias, allows this wage gap to persist without leading to large migration waves. While workers move frequently across firms and regions, job flows and accepted wage offers are biased towards the home region, thus effectively segmenting the two labor markets, and shielding low productivity firms in the East from competition. We estimate the home bias, and use matched employer-employee data to unpack it into three components: preferences, labor frictions, and skills. General equilibrium counterfactuals show that the different sources of home bias have sharp, but distinct, effects on aggregate wages and on workers' utility.

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[†]33 Liberty Street, New York, NY 10045, email: sebastian.heise@ny.frb.org.

[‡]9500 Gilman Drive #0508, La Jolla, CA 92093-0508, email: tporzio@ucsd.edu.

1 Introduction

In many countries, substantial wage differences across regions have persisted for decades.[1] Examples are the case of the Italian Mezzogiorno, Andalusia in Spain, and the East of Germany. The absence of wage convergence across regions seems puzzling because, in theory, worker flows from low- to high-wage regions should eliminate the gap since barriers to migration are presumably low within countries. In fact, in many cases the wage gaps persist despite sizeable labor mobility across regions.[2]

In this paper, we use detailed micro data from Germany, interpreted through the lens of a new model of worker reallocation across regions and firms, to study why and how wage gaps can persist in spite of labor mobility. We show that the wage gap between East and West Germany can be sustained without leading to large net migration flows due to the fact that workers' mobility is distorted towards the region in which they lived when they first entered the labor market, which we refer to as their *home region*. While workers move frequently, they are relatively more likely to accept job offers from their home region, even at the cost of wage losses. This "home bias" not only distorts labor flows, but also allows unproductive firms in the East to survive since it partially shields them from the competition of more productive firms in the West. We conclude that, in the presence of exogenous productivity differences across regions, home bias can sustain large wage gaps as a persistent equilibrium outcome, and without producing large migration waves across regions.

Germany is an ideal laboratory to study persistent spatial wage gaps in an environment of high worker flows: as Figure 1a illustrates, a sizeable real wage gap of 26% persists between East and West Germany until today, with a discrete change at the former East-West border. However, workers in Germany are very mobile: 30% of workers that entered the labor market for the first time while living in East Germany have spent some time working in the West throughout their observed life until today, and 8% of workers that started in West Germany have spent time in the East. Despite high mobility, a worker's home region has a strong impact on workers' wages. Figure 1b shows workers' real wage today plotted by workers' home county. The wage gap by initial home region is 31%, similar to the regional one.[3] While in principle there could be several mechanisms that explain the two figures, for example West German workers could have higher human capital, we show that – at least in the context of Germany – home bias is the key determinant.

To uncover the origins of the regional wage gap, we draw on matched employer-employee data from the German Federal Employment Agency, together with data on a 50% random sample of establishments in Germany. Using the establishment data, we first verify that the regional wage gap also holds conditional on observables, such as regional differences in industry composition and differences in workers' education or age. We then use a linear wage decomposition as in Abowd, Kramarz, and Margolis (1999) to show in the matched data that the gap is also not primarily driven by unobservable worker

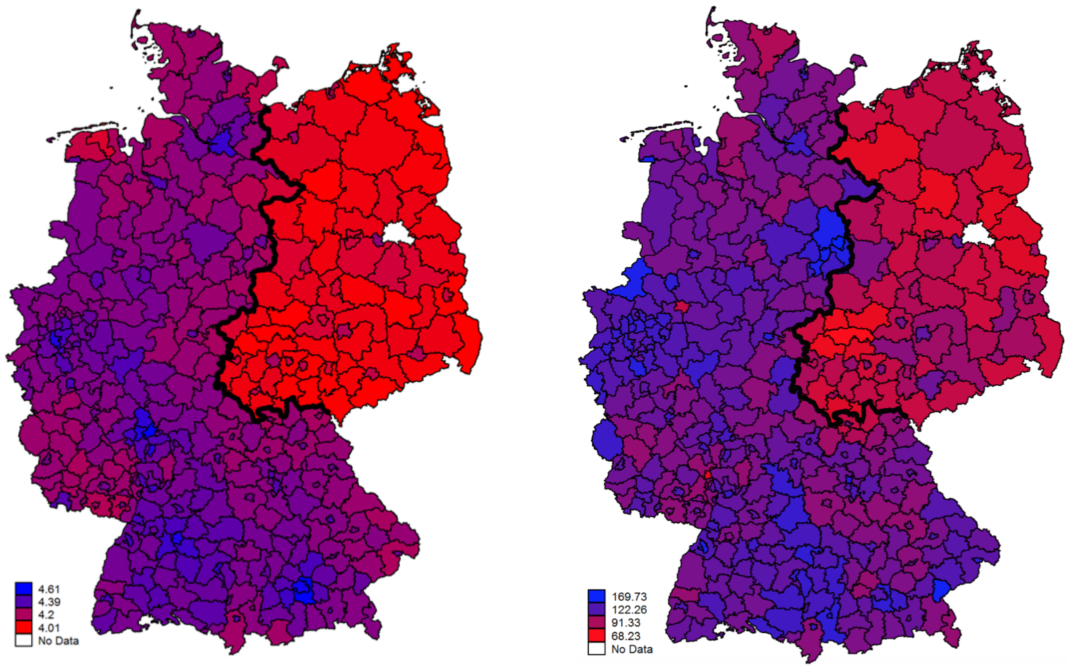
[1] Moretti (2011), Gollin, Lagakos, and Waugh (2014), Redding and Rossi-Hansberg (2017).

[2] For example, e.g., Eckert and Peters (2018) or Fallick and Fleischman (2004) show that large gross flows between U.S. regions coexist with minor net flows, insufficient to arbitrage away wage differences.

[3] Wage gap by home county, as we will explain in detail below, is based on a smaller sample of observations than the wage gap by region. This is reflected in the higher noise of Figure (1b).

Figure 1: Average Real Log Daily Wage, 2009-2014

(a) By County (b) By County of Labor Market Entry



Notes: Average daily log wages are obtained from a 50% random sample of establishments via the Establishment History Panel (BHP) (left) and from matched employer-employee data (LIAB) (right) of the Institute for Employment Research (IAB). Wages are adjusted by county-specific price levels from the Federal Institute for Building, Urban Affairs and Spatial Development (BBSR) in 2009, and deflated forward and backward 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.

characteristics. We find that the establishment component of the decomposition explains about two thirds of the wage gap: East German establishments pay a 17% lower real wage per efficiency unit. We next analyze the wage gap by workers' home region, and show that the results are similar. Workers that start their career in the East are on average employed at establishments that pay 16% less that the establishments at which West German individuals work. Almost all of this effect arises because East German individuals work in the East. While East German workers also have a lower individual component of wages, suggesting differences in human capital or wage discrimination, our results thus indicate that East German workers could realize substantial wage gains from moving West.

Both geographical frictions or home bias could prevent East workers from moving West. We analyze the role played by each by examining workers' mobility patterns and show that despite the high cross-regional mobility, more than half of workers that move out of their home region eventually return. More formally, we estimate a gravity equation that explains worker flows between counties as a function of origin and destination county characteristics, distance, whether a worker crosses between regions, and workers' home region. We find that workers are almost as likely to move between counties across the East-West border as between similar counties within each region, indicating that geographical frictions at the East-West border are unlikely to be a driver of the wage gap. On the other hand, workers are "attracted" to their home region, indicating that home bias plays an important role. Job switchers are 70% more likely to move to a given county if it is in their home region, and are five times less likely to leave such a county.

Further, we examine the wages of workers that move across regions relative to stayers. We find that workers earn a large premium when leaving their home region: moving from East to West, East workers experience on average a 14pp larger wage gain than West ones; while moving from West to East, East workers experience a 18pp smaller wage gain than West ones. By revealed preferences, this finding shows that workers attach a high value to working in their home region. Survey evidence from German households suggests that the home bias we identify is in fact a bias towards the region in which the worker was born and educated. On the other hand, we do not find evidence that East workers have a comparative advantage when they stay in their home region. Using an extended AKM framework, we show that East workers employed at the same establishment in the West as West workers with the same individual component receive the same wage.

We perform several exercises to shed further light on the mechanism driving this home bias. First, we document 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. Second, following the identification strategy of Burchardi and Hassan (2013), we show that East workers moving to the West are more likely to move to counties that already contain a significant number of East individuals. Finally, we show that while individuals are also strongly attached to their home state, there is a significant additional effect working through ties to the overall birth region (East or West).

While the empirical analysis suggests that home bias might be a relevant factor influencing workers' allocation across regions and firms and hence the wage gaps we observe, the analysis does not allow us to quantify the importance of home bias or to unpack it into its different components. We therefore develop a model with three objectives. First, the model allows us to map the observables differences between East- and West-born workers into interpretable primitive parameters. Second, the model allows us to compute the fraction of the observed wage gap between East- and West-born that can be generated by the home bias alone, once we discipline its strength using the empirical moments. Third, the model provides a laboratory to perform counterfactual analysis in general equilibrium, taking into account firms' endogenous response to changes in the labor supply.

The nature of our data calls for a model with two types of labor reallocation: (i) spatial movements across East and West Germany; (ii) reallocation within each region across heterogeneous firms. Our main building block is a standard heterogenous firm job-posting model à la Burdett-Mortensen (e.g., Burdett and Mortensen (1998)), which we extend to a setting with an arbitrary number of regions and arbitrary many worker types. Each region is characterized by an exogenous productivity distribution of firms. Each worker type is characterized by a vector of region-specific skills, preferences, and wedges that define the relative chance of receiving a job offer from a given region. Firms choose their optimal wage and decide how many job vacancies to open, subject to a region-specific cost. Workers randomly receive offers and accept the offer that yields the higher utility, moving across firms both within and across regions. We derive a tractable solution represented by a system of two sets of differential equations with several boundary conditions.

In the model, three sources of home bias generate spatial frictions which keep the two labor markets, the one for East- and the one for West-born, apart. Workers' location preferences lead workers to accept only the particularly high wage offers arriving from the foreign region. Workers' skills may also lead to a segmented labor market, as long as workers have a comparative advantage for their home region, thus leading them to find more appealing offers there. Last, workers flows across regions may be mechanically biased by a lower probability of receiving offers from the foreign region, which could be interpreted as either discrimination in firm hiring, or the role of referrals and networks in the search process.

While each one of the three sources of home bias could in principle keep the two labor markets apart, the model shed lights on how matched-employer employee data can be used to separate their roles. In fact, the same regressions that we run in the empirical part allows us to quantify and unpack the sources of home bias. First of all, the model delivers an AKM type regression, which directly pins down – without the need to estimate the model – the East- and West-born average skills. As we already mentioned, West workers have a higher unobservable component, but skills are transferable across regions, hence, the estimated skills do not lead to home bias. The preference and frictions home bias are instead estimated jointly with all other paramaters through simulated method of moments. We target the estimates of wage gains within and across regions, and the home bias in job to job flows. We estimate a sizable home bias in preferences: workers value a one dollar earned in the foreign region as approximately 85 to 90 cents earned in the home region. We also estimate a sizable distortion in the arrival rate of offers, with workers receiving 4 times as many offers from their home region.

Finally, we use the estimated model to perform several quantitative exercises. First, we use the model to quantify how much of the observed differences in wages between East- and West-born workers is due to the home bias, rather than to mobility frictions, which are not included in the model. The model matches, by construction, the wage gap between East and West firms, but not the one between the firms where East and West workers are employed. The model predict that the latter is approximately half than the one we observe empirically. In other words, the model predicts that even in the very long-run, hence after Germany has reached a steady state with no net migration, still East-born workers would work at firms that pay 8-10pp lower wages. Second, we study the counterfactual of removing the two different sources of home bias. We show that the wage gap between East and West would reduce, but would not disappear, since reallocation frictions across firms are themselves sufficient to allow low productivity firms in the East to survive. However, the share of population working in the East would reduce dramatically. We also show that understanding whether the observed wage gap by birth-region is driven by home bias in preference or labor frictions changes the mapping between observed wage gaps and unobserved utility gaps.

Literature. We are not the first to study spatial wage gaps. A large literature, at least since the work of Harris and Todaro (1970) on the rural-urban wage gap, has sought to explain the large observed differences in average wages across space. The literature can be broadly divided into two sets of papers. The first category assumes free labor mobility and homogenous workers and solves for spatial equilibria along the lines of the seminal work by Rosen (1979), Roback (1982), and more recently of Allen and Arkolakis (2014). The assumption of a spatial equilibrium implies that utility is equalized across space, and therefore the observed differences in wage gaps are simply a reflection of differences in local amenities. The second category, instead, has studied spatial wage gaps as a possible symptom of misallocation of labor across space. A core debate in this literature has been to distinguish between sorting of heterogenous workers based on their comparative advantages and frictions to labor mobility that generate wedges along the lines of the work by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009).[4] Our paper belongs to this second category of papers. As the more recent work in this literature, we allow for both unobservable ability and frictions to explain the wage gap between East and West Germany. Our main contribution is to focus on one spatial wedge, namely home bias, and unpack it into several components, thus opening up the black box of labor mobility frictions. In order to pursue this task we apply the toolset and the datasets of the frictional labor literature. In particular, our model adapts the work of Burdett and Mortensen (1998) to a setting with a non-trivial spatial dimension. Moreover, we rely on matched employer-employee data , as now common in the labor literature,[5] and we show that they are crucial to distinguish spatial frictions from the general reallocation frictions across firms, which are the focus of the labor literature. From a purely methodological perspective, our paper bridges the gap between the macro-development misallocation literature and the frictional labor literature. We are – to the best of our knowledge – the first to use the tools of the latter within the context and research questions of the former.

Our work is informed by, and consistent with, the rich literature on migration. The idea that worker identity may be an important drivers of migration decisions is at least as old as the work of Sjaastad (1962), and more recently has been revived by the structural approach of Kennan and Walker (2011). This work has documented an important role for home preferences in explaining the dynamics of migration choices. Our contribution is to show more direct evidence for home bias, and unpack it into its several components. A task that we can accomplish due to the use of richer, matched employer-employee data.

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 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, 2002, 2006), Fuchs-Schündeln, Krueger, and Sommer (2010)). We use matched employer-employee data to examine the role of worker sorting, productivity differences, spatial, and reallocation frictions in a unified framework; a task that has not been attempted before.

[4] See for example Bryan and Morten (2017); Young (2013); Hicks, Kleemans, Li, and Miguel (2017).

[5] See for example Card, Heining, and Kline (2013).

2 Data

We use five distinct datasets. Our most important data source are two confidential micro datasets provided by the German Federal Employment Agency (BA) via the Institute for Employment Research (IAB). First, we use establishment-level data from the Establishment History Panel (BHP). This dataset contains 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. The data are based on mandatory annual social security filings. Government employees and the self-employed are not covered. The BHP defines an establishment as a company's unit with at least one worker liable to social security operating in a distinct county and industry.[6] Throughout the rest of this paper, we use the terms establishment and firm interchangeably to refer to these entities. For each establishment, the dataset contains information on the establishment's location, number of employees, employee structure by education, age, and occupation, and the wage structure in each year. The data are recorded as annual cross-sections since 1975 for West Germany and since 1991 for East Germany, which we combine to form a panel covering about 650,000 to 1.3 million establishments per year.

The second 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 1.5 million individuals drawn from the Integrated Employment Biographies (IEB) of the IAB, which cover employment and socio-economic 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 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 recorded covering 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.

Our third dataset is the German Socio-Economic Panel (SOEP), a longitudinal annual survey of around 30,000 individuals in Germany since 1984. The data provide information about an individual's family, living conditions, and education history, in addition to employment information. Importantly, the data contain information on whether an individual grew up in East or in West Germany, for two subsamples. First, the initial wave of individuals drawn in 1984 covered only West German individuals, while in 1990 another wave of exclusively East German individuals was drawn. We will analyze

[6] 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)).

individuals from these waves still in the data in 2009-2014 below, referring to this sample as the "old sample". Second, for those individuals that entered the survey while they were still in their childhood, the data contain information on the location of individuals' pre-school, primary school, or secondary school. We refer to individuals with such information that began high-school after the reunification as the "young 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 in 2009 assessing regional price variation across 393 German micro regions covering all of Germany that correspond to counties or slightly larger unions of counties.[7] The data cover about two thirds of the consumption basket, including housing rents, food, durables, holidays, and utilities. Figure 14a in Appendix F shows the map of county-level price levels, and shows that East Germany on average has lower prices.

The final dataset used are publicly available county-level unemployment rates from the Federal Employment Agency.

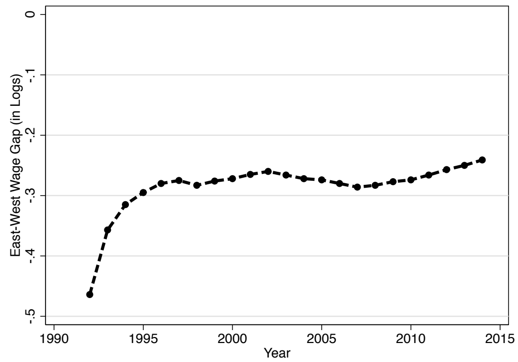
Our core period of analysis is 2009 to 2014, the last year available in the IAB data, to focus on persistent differences between East and West Germany. For some empirical specifications that require a longer sample, we will use the years 2004 to 2014. We adjust all wages in 2009 based on the BBSR's local price index, and deflate the 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 analyses below will use full-time workers only.

3 Empirical Evidence of the Enduring Divide

In this section, we use our rich datasets to document three sets of results. First, we show that there are persistent real wage differences between East and West Germany, which arise because establishments in the West pay higher wages. Second, we investigate whether workers that lived in the East when first entering the labor market take advantage of this wage gap by moving to the West. We find that the average wage gap between an East and a West German worker is in fact similar to the regional wage gap, largely because workers that start their career in the East work at establishments paying less and are mostly employed in the East. The wage gap holds even conditional on workers' observable and unobservable characteristics, as estimated by individual fixed effects. Finally, we show that the wage gap is not primarily due to a lack of mobility but because of "home bias", which we define as workers' being relatively more attracted to their home region, irrespective of their current location. We explore empirically three mechanisms behind this bias: comparative advantage towards the home region, differences in the arrival rate of job offers, and a preference to live in the home region, and

[7] 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.

provide evidence for the latter two channels: workers' job-to-job flows conditional on distance and amenities are relatively biased towards the home region, and workers are paid significant wage premia to move away from home. We provide some additional results for interpretation and robustness, and will interpret the channels structurally through a model in Section 4.

3.1 Wage Differences by Region

Despite the absence of a physical border, language difference, or barrier between East and West Germany since the reunification in 1990, a sizable and sharp real wage gap remains. Figure 1a plots the average daily wage from the BHP, adjusted for cost-of-living differences from the BBSR survey, for each county in Germany.[8] Figure 2 illustrates that the real wage gap has been closing very slowly since the mid-1990s.[9] The large wage gap is not driven by a few outlier counties: Figure 15 in Appendix F shows that close to 80% of the West German population is living in counties with a higher average real wage than the highest-paying county in the East.

To more formally establish the size of the regional wage gap, we use data from our core sample period (2009-2014) and 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 weigh by establishment size since we are interested in the average wage gap in Germany. Table 1 presents the estimates for γ.[10] Column (1) shows that the unconditional wage gap is 26%. In column (2), we additionally control for the establishment's average share of male workers to account for gender

[8] Appendix A provides a brief discussion of the reunification process. Figure 14b in Appendix F shows that there is also a sharp difference in unemployment across the two regions.

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

[10] Table 1 in Appendix G provides the unweighted estimates.

Table 1: Effect of Region on Real Wage

$\bar{w}_{jt}$	(1)	(2)	(3)
$\mathbb{I}_{j,East}$	$-\mathbf{.2609}^{***}$	$-\mathbf{.2467}^{***}$	$-\mathbf{.2052}^{***}$
	(.0074)	(.0031)	(.0027)
Year FE	Y	Y	Y
Observable controls	–	Y	Y
Industry FE	–	–	Y
Observations	4,797,798	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.

differences, the share of workers that are older than 55 and the share of workers that are younger than 30, the share of workers with a college degree, and the log of establishment size. With these controls the gap narrows slightly, to 25%. Column (3) of Table 1 includes industry fixed effects to control for differences in industry structure, which narrows the gap slightly further. We provide more information on the college, gender, and industry controls in Figures 16a-16 in Appendix F, 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 countries, irrespective of their average level of education, and across all industries, and that the wage gap also holds across counties with different gender composition.

While the previous regression controls for observables, it is possible that unobservable skill differences could explain the gap if more skilled workers sorted into West Germany.[11] To rule out this possibility, we turn to the individual-level LIAB data and perform a decomposition of the wage gap into worker and establishment-specific factors. We fit in the data a linear model with additive worker and establishment fixed effects, as originally in Abowd, Kramarz, and Margolis (1999) and, more recently, in Card, Heining, and Kline (2013),

$$w_{it} = \alpha_i + \psi_{J(i,t)} + BX_{it} + \epsilon_{it}, \tag{2}$$

where w_{it} denotes the log wage of individual i that is employed by firm j at time t, α_i is a worker-specific component, $\psi_{J(i,t)}$ is a component specific to the establishment at which the worker is employed, and X_{it} is a vector of controls. We follow the specification in Card, Heining, and Kline (2013) exactly, but fit the model to both East and West Germany. We provide more details on the specification in Appendix C. As is standard, we estimate the model on the largest connected set of workers in our data, since identification of workers and establishment fixed effects requires firms to be connected through workers flows.[12] This sample includes approximately 97% of West and East workers in the LIAB. Given

[11] Sorting has been shown to explain a consistent share of spatial wage gaps in several contexts, see for example Glaeser and Mare (2001); Combes, Duranton, and Gobillon (2008); Hicks, Kleemans, Li, and Miguel (2017); Young (2013)

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

Table 2: AKM Decomposition Results

		Regional Gap		Birth Gap	
		(1)	(2)	(3)	(4)
		$\hat{\beta}$	*s.e.*		
(1)	Establishment FE ($\hat{\psi}_{J(i,t)}$) (no controls) ($\hat{\psi}_{J(i,t)}$)	$-$**.1691*****	(.0186)	$-$**.1558*****	(.0147)
(2)	Establishment FE ($\hat{\psi}_{J(i,t)}$)	$-$**.1609*****	(.0179)	$-$**.1450*****	(.0136)
(3)	Worker FE ($\hat{\alpha}_i$) (no controls)	$-$**.1317*****	(.0010)	$-$**.1278*****	(.0010)
(4)	Worker FE ($\hat{\alpha}_i$)	$-$**.1084*****	(.0009)	$-$**.1061*****	(.0010)
(5)	Point estimates on $\mathbb{I}_i^{(b=\text{East};\, r=\text{West})}$			.0190	

Notes: $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the establishment level for rows (1)-(2) and at the individual level for rows (3)-(4).

the estimated coefficients, we perform a projection

$$\hat{y}_{ij} = \rho_i + \beta \mathbb{I}_{j,East} + \gamma X_i + \varepsilon_{ij}, \tag{3}$$

where $\hat{y}_{it}$ is either the estimated worker or establishment component, $\hat{\alpha}_i$ or $\hat{\psi}_j$, $\mathbb{I}_{j,East}$ is a dummy for whether establishment j is located in East or West Germany, and X_i are controls for age, gender, and a college dummy. The coefficient β identifies whether there are systematic differences in the worker or establishment component between workers employed in East and West Germany.

Columns (1) and (2) of Table 2 display the results from these projections. Rows (1) and (2) show that there are large differences in the establishment component regardless of whether the controls are included. The average East German establishment component is about 17% lower than the one for a West German establishment. The average worker component differs as well, but by less. Thus, the majority of the wage gap is accounted for by the fact that establishments located in the East pay lower wages to identical workers than those in the West.

3.2 Wage Differences by Home Region

We next examine whether a wage gap also exists between workers that begin their career while living in East and in West Germany, respectively. We classify an individual as initially living in the East (West) if at the first time she appears in our entire dataset since 1993, in employment or unemployed, her location of residence is in the East (West). Prior to 1999, we use the worker's first job's establishment location since the residence location is unavailable. We refer to the region of the first observation as the individual's "home region". We show below in the SOEP data that we can interpret an individual's home region as the region of the individual's birth or childhood upbringing.

We begin by running wage regressions similar to before at the individual level,

$$w_{it} = \gamma \mathbb{I}_i^{East} + GX_{it} + \delta_t + \epsilon_{it}, \tag{4}$$

Table 3: Effect of Home Region on Real Wage

w_{itbr}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{I}_i^{East}$	$-$**.3121*****	$-$**.2744*****	$-$**.1803*****	$-$**.0444*****	$-$**.0361*****	$-$**.1396*****	$-$**.0981*****
	(.0014)	(.0013)	(.0009)	(.0015)	(.0014)	(.0024)	(.0022)
$\mathbb{I}_{j,East}$						$-$**.2025*****	$-$**.2703*****
						(.0057)	(.0056)
$\mathbb{I}_i^{East}\ \mathbb{I}_{j,East}$						$-$.0102	**.0659*****
						(.0062)	(.0061)
Year FE	Y	Y	Y	Y	Y	Y	Y
Age/educ/gender	–	Y	Y	Y	Y	–	Y
Industry	–	–	Y	Y	–	–	–
Ind + county	–	–	–	Y	–	–	–
Ind × county	–	–	–	–	Y	–	–
Observations	7,554,910	7,554,910	7,554,898	7,554,898	7,554,898	7,554,910	7,554,910

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

where $\mathbb{I}_i^{East}$ is now a dummy that is equal to one if the individual's home region is East Germany and X_{it} are individual characteristics. Column 1 of Table 3 shows the coefficients from this regression without controls. We find a real wage gap between an average East and West German worker of 31%. Thus, an individual's home region has a persistent effect on her labor market outcomes. In Column 2 of Table 3, we run the wage regression with additional controls for age, schooling, and gender, which reduces the coefficient slightly. In column 3, we add 3-digit industry fixed effects, and in column 4 we further add county fixed effects. In column 5, we run our most stringent specification which includes industry times county results and find a similar wage gap. Even when working within the same county and industry, similar East German workers receive a 4% lower real wage than West Germans. Table 11 in Appendix G presents the results separately for individuals working in East and West Germany and shows that the wage gap exists in both regions. Tables 12-14 in Appendix G show the results for different age cohorts and illustrate that the wage gap is larger for older workers.

To control for unobservale worker characteristics, similar to before we next project the fixed effects from the AKM decomposition (2) on a dummy for whether an individual was born in the East, rather than a region dummy, via equation (3) (Columns (3) and (4) of Table 2). Rows (1) and (2) indicate that the establishment component accounts for slightly more than half of the wage gap in the LIAB. Thus, East-born workers work for establishments paying significantly lower wages than comparable West German workers. Rows (3) and (4) show that the individual component is also important, leading to a gap of 11%. This difference could be attributed for example to lower human capital of East German workers or wage discrimination. Table 15 in Appendix G peforms that decomposition separately for workers of different age cohorts and shows that the gap in the individual component between East and West German workers is significantly higher for older workers, consistent with a longer exposure of

Table 4: Home Region and Birth Region in the SOEP

	Old SOEP Sample				New SOEP Sample			
w_{it}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{I}_i^{East}$	$\mathbf{-.3495}^{***}$	$\mathbf{-.4054}^{***}$			$\mathbf{-.1586}^{***}$	$\mathbf{-.1485}^{***}$		
	(.0214)	(.0198)			(.0319)	(.0302)		
$\mathbb{I}_i^{East,b}$			$\mathbf{-.3376}^{***}$	$\mathbf{-.4041}^{***}$			$\mathbf{-.1221}^{***}$	$\mathbf{-.1173}^{***}$
			(.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. $\mathbb{I}_i^{East,b}$ is a dummy for a worker's birth region or schooling region.

East German workers to a different education system.

East German workers mostly work for establishments paying low wages because they remain in their home region. We run regression (4) with a dummy for whether the worker's firm is located in the East and an interaction term,

$$w_{it} = \gamma \mathbb{I}_i^{East} + \rho \mathbb{I}_{j,East} + \omega \mathbb{I}_i^{East} \mathbb{I}_{j,East} + GX_{it} + \delta_t + \epsilon_{it}, \tag{5}$$

providing us with estimates, presented in Columns (6) (without controls) and (7) (with controls) of Table 3, for the wage gap relative to West workers employed in the West. Using the fact that during our sample period about 66% of individuals are West workers in the West, 2% are West workers in the East, 5% are East workers in the West, and 26% are East workers in the East, we can attribute about 85% of the wage gap by home region to East workers working in the East. Thus, the cause of the persistent wage gap appear to be either substantial geographical frictions that prevent movements between regions, or because there is an identity-based mobility friction that draws workers back to their own region.

To shed light on the source of workers' regional preference, we use survey evidence from the SOEP, and demonstrate that workers' region of initial labor market entry is mostly identical to the region in which the worker grew up. We begin with the old SOEP sample. This sample has the advantage that the birth region of the worker is known with certainty. We compute the home region in the same way as in the LIAB, and find that for 88% of workers born in East Germany and 99% of workers born in the West this imputed home region corresponds to their birth region. In the young sample, which is based on the smaller set of individuals for which we observe some of their education and the beginning of their career, we do not observe the birth region. Instead, we compute the region in which we observe the earliest schooling for the individual up to the start of high-school. The imputed home region matches to the true region of schooling in 92% and 99%, respectively, in this sample. We then run the wage

Table 5: Summary Statistics on Mobility

		(1) Home: West			(2) 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

regression (4) using alternatively an East dummy based on our definition of home region, $\mathbb{I}_i^{East}$, and an East dummy based on the birth / early schooling region, $\mathbb{I}_i^{East,b}$. Table 4 presents the results. We find that the results using imputed home region and birth region are very similar: for example, in the old sample, controlling for observables the East-West wage gap is .405 using the imputed home region and .404 using the true birth region. Thus, it appears that we can interpret workers' bias towards their home region as a bias towards their childhood region. The East-West gap is larger in the old sample, possibly reflecting that East and West workers in this sample were educated under different social systems.

We next show that in fact there is substantial mobility across regions, and then demonstrate that workers exhibit home bias.

3.3 Geography Versus Home Bias

Table 5 presents some statistics on cross-regional mobility in Germany 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 in their non-home region. Figure 17a in Appendix F shows the total stock of workers in the other region over time, which has been increasing at a declining rate. Overall, of the workers in our sample, 8% of East-born and 30% of West-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, and workers on average spend only 3 years in the other region (row 4). In fact, Figure 17b in Appendix F shows that the net flows of workers moving away from their home region are close to zero. The final three rows present some characteristics of workers that never left their home region, have moved to the other region, and that have returned. We find that movers tend to be more educated and more likely to be male compared to workers that stay.[13]

[13] 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 16 in Appendix G shows the statistics separately by move date of the workers.

We demonstrate more formally that workers' mobility is biased towards their home region by estimating 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 will show that geographic barriers do not play a role, while regional identity does.

Let $h^b_{o,d,t}$ be the total number of workers born in region b 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. We compute the share of workers from county o moving to county d across all years in our core period as

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

where $\mathbb{D}$ is the set of all the 402 counties in both East and West Germany.[14] We use these shares to fit the gravity equation

$$\log s^b_{o,d} = \delta_o + \gamma_d + \alpha \mathbb{I}^{East} + \sum_{x \in \mathbb{X}} \phi_x D_{x,o,d} + \sum_{k \in \mathbb{K}} \beta_k \mathbb{I}^k + \epsilon^b_{o,d}, \tag{6}$$

where δ_o and γ_d are county of origin and destination fixed effects, which capture the fact that some counties may be more attractive than others, either due to better market conditions or higher amenities. For example, if γ_d is high for a destination then a high share of workers move into that county regardless of their origin location or identity. The dummy $\mathbb{I}^{East}$ is equal to one if a worker's home region is East Germany, and $D_{x,o,d}$ are dummies for buckets of distance travelled between origin and destination. The set of buckets $\mathbb{X}$ contains 50km intervals from 50km-100km onward to 350km-400km, and an eighth group for counties that are further than 400 km apart. Finally, the set $\mathbb{K} = \{R(o) \neq R(d), R(o) = b, R(d) = b\}$ captures our key objects of interest. The term $\mathbb{I}^{(R(o) \neq R(d))}$ is a dummy for cross-region moves, which captures geography, picking up whether workers are less likely to move across regions regardless of where they were born. The dummies $\mathbb{I}^{(R(o)=b)}$ and $\mathbb{I}^{(R(d)=b)}$ are dummies that equal one when the origin county and the destination county, respectively, are equal to the home region, and capture home bias. Workers born in the East and West may be attached to their respective home region, either due to preferences, comparative advantages, or possibly due to a social network that allows them to find job opportunities. If the identity of the worker does not matter, then the coefficients on these latter two dummies should be equal to zero.

Table 6 presents the estimates from regression (6). We find that workers are more likely to move to nearby counties, which corresponds to the standard gravity result in the trade and labor literatures. Importantly, the identity dummies are highly significant and much larger than the cross-border dummy, which is basically zero. The origin dummy implies that a worker for whom o is in the birth region is

[14] 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 is standard in the literature, note that we observe flows for the majority of pairs.

Table 6: Gravity

	$\hat{\beta}$	s.e.		$\hat{\beta}$	s.e.
$\mathbb{I}^{East}$	**.1564*****	(.0071)	$\phi_{300-350}$	$\mathbf{-3.0074}^{***}$	(.0189)
ϕ_{50-100}	$\mathbf{-1.8128}^{***}$	(.0187)	$\phi_{350-400}$	$\mathbf{-3.0536}^{***}$	(.0191)
$\phi_{100-150}$	$\mathbf{-2.5488}^{***}$	(.0184)	ϕ_{400+}	$\mathbf{-3.1369}^{***}$	(.0187)
$\phi_{150-200}$	$\mathbf{-2.8004}^{***}$	(.0184)	$\mathbb{I}^{(R(o)\neq R(d))}$	**.0265*****	(.0081)
$\phi_{200-250}$	$\mathbf{-2.9121}^{***}$	(.0185)	$\mathbb{I}^{(R(o)=b)}$	$\mathbf{-1.6285}^{***}$	(.0065)
$\phi_{250-300}$	$\mathbf{-2.9669}^{***}$	(.0187)	$\mathbb{I}^{(R(d)=b)}$	**0.6005*****	(.0065)
	Observations	94,203			

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

about five times more likely to stay than a worker for whom it is not.[15] Similarly, a worker for whom d is in the birth region is about 70% more likely to move there than a worker for whom it is not. In Appendix F, Figure 18a illustrates this effect visually by plotting the normalized coefficients ϕ_x as a function of distance, and Figure 18b illustrates how the curve shifts once either of the two identity dummies is added. Our results imply that a worker is as likely to move 450km from outside to into her home region as she is to move 150km out of her home region. Table 17 in Appendix G presents the coefficients for different sub-groups of the population and shows that the attachment to the home region is weaker for skilled workers and for non-Germans, and that the results continue to hold if we exclude job-to-job transitions through unemployment.

The baseline specification constrains workers' valuation of different counties, captured by the origin and destination fixed effects, to be the same across East and West workers. It also imposes a constant home region effect at any distance. We can relax these assumptions by running a more flexible specification

$$\log s^b_{o,d} = \delta^b_o + \gamma^b_d + \sum_{x\in\mathbb{X}} \phi_x D_{x,o,d} + \xi_{o,d} \sum_{y\in\mathbb{Y}} \psi_y D_{y,o,d} + \epsilon^b_{o,d}, \tag{7}$$

where we now allow the county dummies to be birth region specific, $\xi_{o,d}$ is a dummy that takes value one if counties o and d are in different regions, and $D_{y,o,d}$ is a dummy that takes value one if the shortest distance between county o and the border to the other region falls into distance group $y \in \mathbb{Y}$, where $\mathbb{Y}$ includes four groups: 1-100, 100-150, 150-200, and 200+.[16] If the coefficients ψ_y are negative, workers are less likely to move between two counties if the move involves crossing the border, irrespective of worker home region.

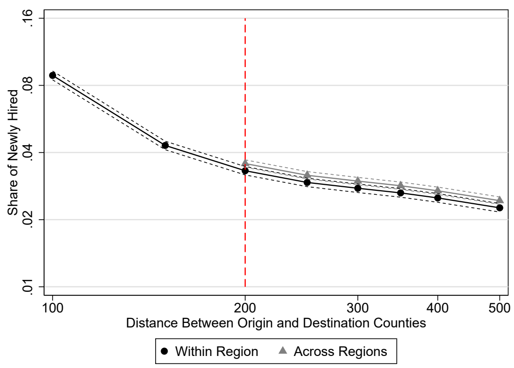
The detailed coefficients from the regression are presented in Table 18 in Appendix G. Given the

[15] The difference in log shares between Home origin and Not Home origin is -1.63, and the shares of workers in Home origin and Not Home origin must add up to one. Solving this system of equations gives shares of flows of 0.35 and 0.65, respectively.

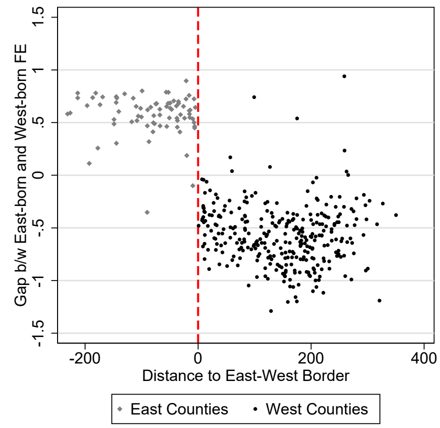
[16] We measure the distance to the border as the distance to the closest county in the other region.

Figure 3: Geography versus Identity

(a) Geography



(b) Identity: Destination FE



number of coefficiens involved, we instead illustrate the results by plotting in Figure 3a, for an average county situated at 200 km from the regional border, the share of workers that would be hired by a county in the same region at distances $x \in \mathbb{X}$ (the coefficients ϕ_x) and by a county in the other region at distances $x \in \mathbb{X}$ for $x \geq 200$ (the coefficients $\phi_x + \psi_y$), taking the origin and destination effects as constant.[17] The lines are almost on top of each other. Thus, conditional on distance and fixed effects, there is no geographical border friction, as workers are as likely to move between counties within regions as across regions. On the other hand, Figure 3b shows the effect of worker identity. For each county, we compute the difference between the destination fixed effect for workers with home region East and West, respectively, and plot the resulting fixed effect differences as a function of the county distance to the East-West border, defined so that East counties have negative distance.[18] The figure shows a sharp border effect: 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 workers are less likely to move to counties in the West. Figure 19 in Appendix F presents the origin fixed effects, and highlights that workers are also less likely to move out of counties in their home region.[19] The results imply that both East and West workers have a strong "home bias".

[17]We need to fix border distance since the friction depends on it, for any distance travelled.

[18]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, relatively 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.

[19]Figure **??** in Appendix F highlights that both origin and destination fixed effects are strongly correlated for East and West Germans. Thus, both agree on which counties are more attractive, but East-born are simply less attracted to all counties in the West.

3.4 Home Bias in Worker Wages

We now perform a regression of wage changes between employment spells and demonstrate that workers receive substantial wage premia when leaving their home region. We define job switches as cases where a spell of full-time employment at one establishment is succeeded by full-time employment at another establishment, including cases where the two are separated by a spell of non-employment.[20] Let $d_{it}^{EE,h}$ and $d_{it}^{WW,h}$ be dummies that are equal to one if worker i with home region h makes a job-to-job move within the East (EE) and within the West (WW), respectively, at time t. For cross-region switches, we define two types of moves: migration and commuting. In the former, the worker changes her job and residence location, while in the latter only the job location is changed. The distinction is useful because we expect that workers that can 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 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 in the year following the move. The remaining cases are defined as commuting. Let $d_{it}^{EW,h,m}$ and $d_{it}^{WE,h,m}$ be dummies for migration from East to West and from West to East, respectively, for workers from home region h. Denote by $d_{it}^{EW,h,c}$ and $d_{it}^{WE,h,c}$ analogous dummies for commuting.

Let $\mathbb{L}$ be the set of the six superscripted types of moves for the two types of workers. We run the specification

$$\Delta w_{it} = \alpha_1 \mathbb{I}_i^{East} + \alpha_2 \mathbb{I}_{j,East} + \alpha_3 \mathbb{I}_i^{East} \mathbb{I}_{j,East} + \sum_{l \in \mathbb{L}} \beta_l d_{it}^l + BX_{it} + \epsilon_{it}, \tag{8}$$

where Δw_{it} is worker i's wage change between two job spells, $\mathbb{I}_i^{East}$ is a dummy for whether the worker was born in the East, $\mathbb{I}_{j,East}$ is a dummy for whether the establishment associated with the earlier spell is in the East, and X_{it} is a set of controls. The omitted category is the within-firm wage growth.

Table 7 presents the estimates for migration. Column (1) shows the results with only a year dummies. We find that a worker's real wage gain from leaving her home region is significantly larger than the wage gain from returning. For example, when moving West-to-East, West-born workers receive a 21% wage increase relative to their average wage growth within an establishment, while East-born workers obtain only 1%. In comparison, West-born workers obtain a 5 percentage point smaller gain when they move East-to-West, while East-born workers experience a 36 percentage point larger increase. We summarize the size of the home bias in row (5) by taking the difference between the two. This figure is the sum of the wage premia of East and West home region leavers relative to East and West returners, and amounts to 40.7%, indicating substantial home bias. We report the detailed coefficients for commuting in Table 19 in Appendix G, and present in row (6) only the implied home bias. As expected, the relative bias for commuting is only about one tenth as large as the one for migration, since workers do not need to be compensated for moving residence. Table 19 also presents the wage gains for within-region job switches and shows that they are larger in the West, and similar

[20] We analyze alternative definitions of job switches in robustness exercises below.

Table 7: Effects of Migration

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Δw_{it}			Δ Complex	Δ Est. FE
(1)	$d_{it}^{EW,W,m}$	**.1662*****	**.1551*****	**.1853*****	**.1684*****	**.1906*****	$-.0363$	**.1152*****
		(.0211)	(.0210)	(.0210)	(.0231)	(.0261)	(.0329)	(.0128)
(2)	$d_{it}^{WE,W,m}$	**.2117*****	**.1937*****	**.2090*****	**.2283*****	**.1902*****	**.2229*****	$-.0183$
		(.0258)	(.0257)	(.0257)	(.0272)	(.0306)	(.0276)	(.0132)
(3)	$d_{it}^{EW,E,m}$	**.3729*****	**.3605*****	**.3684*****	**.3872*****	**.3356*****	**.0428*****	**.1572*****
		(.0130)	(.0129)	(.0130)	(.0147)	(.0150)	(.0155)	(.0066)
(4)	$d_{it}^{WE,E,m}$	.0115	$-.0068$	.0212	**.0277***	.0125	.0092	$-$**.0693*****
		(.0142)	(.0142)	(.0143)	(.0157)	(.0182)	(.0200)	(.0088)
(5)	DiD Migr	$-.407$	$-.406$	$-.371$	$-.419$	$-.323$	$-.293$	$-.093$
(6)	DiD Comm	$-.047$	$-.054$	$-.046$	$-.041$	$-.049$	$-.105$	$-.041$
	Year FE	Y	Y	Y	Y	Y	Y	Y
	Indiv. controls	N	Y	Y	Y	N	Y	Y
	Mobility	N	N	Y	Y	Y	Y	Y
	Ind×Occ×Edu	N	N	N	Y	N	N	N
	Individual FE	N	N	N	N	Y	N	N
	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.

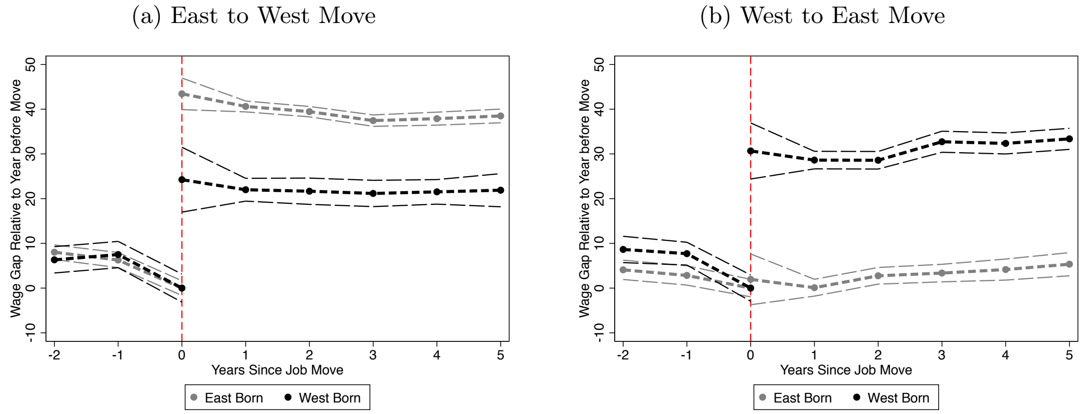
in magnitude to commuting.

The following columns add controls. Column (2) adds controls for gender, age, and a dummy for whether the worker went to college. In column (3), we additionally include dummies for distance, to control for the fact that moves over longer distances may yield larger wage gains, and dummies for the number of prior job-to-job moves. In column (4), we include (industry×occupation×college) fixed effects. Column (5) presents the most stringent specification, which includes individual fixed effects. We refer to this specification as our benchmark. Overall, we find evidence for significant home bias, as workers leaving their home region receive relatively larger wage gains. Table 20 in Appendix G presents benchmark estimates for different sub-groups and shows that the results are consistent, though we do not find home bias for older workers.[21] We also do not find home bias for non-Germans, which makes sense since these are presumably less attached to specific regions in Germany.

We shed light on whether the wage increases are systematically related to job attributes by running our benchmark specification with changes in job characteristics on the left-hand side. First, we analyze whether wage gains at migration are compensation for a more demanding job by using occupational

[21] 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.

Figure 4: Wages



complexity as left-hand side variable.[22] Second, we analyze whether the wage gains are associated with employment at a better establishment by using the establishment fixed effects from the AKM model instead. Columns (6)-(7) of Table 7 show substantial home bias for both variables. Workers move to significantly more complex jobs upon migration, and East-to-West moves for both workers lead to better establishments. When returning home, East workers move to worse establishments.

We perform several robustness checks. First, we analyze whether our results are sensitive to our definition of job switches. We add 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 21 in Appendix G show that our findings are robust to these alternatives.[23] 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 21 show that the wage gain of commuters falls slightly, as expected, but there is still significant home bias.

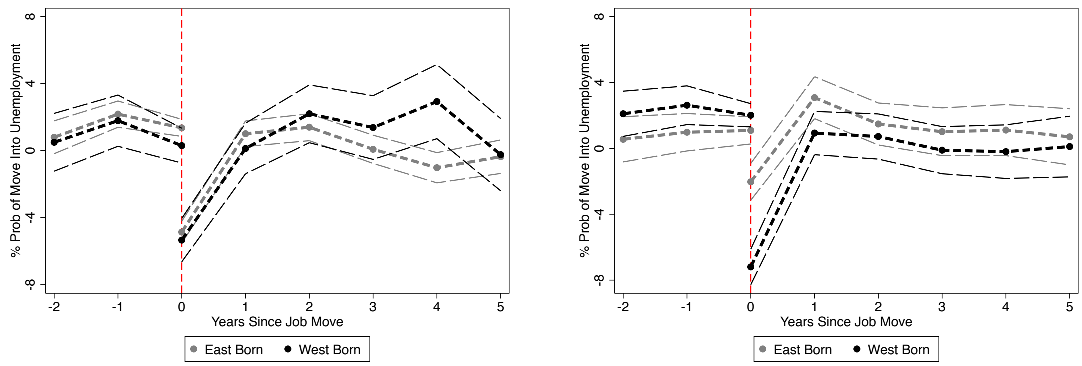
While the previous analysis has demonstrated that migrants obtain substantial wage increases, it cannot yet answer how migration affects workers' wage profile over longer time horizons. To shed light on wage dynamics, we now consider the extended period 2004-2014, and aggregate the data to

[22]Complexity is reported by the employer on a four point scale.

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

Figure 5: Unemployment

(a) East to West Move (b) West to East Move



the annual level by averaging over wage rates of each worker within a year.[24] We then perform local projections by running our benchmark regression repeatedly, where we replace Δw_{it} on the left-hand side with $\Delta w_{i\tau}$ for $\tau = \{t-2, ..., t+5\}$ in the different runs. The regression coefficients indicate how migration in year t affects wage growth in year τ.

Figure 4a plots the estimated wages that are obtained from the migration coefficients $\beta_{EW,h,m}(\tau)$, translated into levels, where we normalize the year just before the migration to zero. Figure 4b presents the wage gains for West-to-East moves. Both figures clearly visualize the relatively larger wage gains of workers that move out of their home region relative to those that return. They also indicate that there are no, or only very small, dynamic gains. Thus, workers do not appear to switch regions in anticipation of larger wage increases in the future. We will model this feature below by assuming that workers' decision to move jobs depends only on the flow wages.

Since the large wage gains could be compensation for a higher risk of unemployment after the move, we run similar regressions with workers' probability of becoming unemployed on the left-hand side (Figures 5a and 5b). While there is a sharp drop in the unemployment probability in the year of the job move, otherwise it is relatively constant before and after the switch, so compensation for unemployment risk does not appear to be present. Moreover, there are no dynamic effects. Appendix F presents analogous figures with individual fixed effects.

3.5 Home Bias in Skills

We finally evaluate whether a comparative advantage keeps workers in their home region. For this purpose, we re-run the AKM specification, but add in an additional term $\mathbb{I}_i^{(b=\text{East};\, r=\text{West})}$, which captures

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

whether an East-born worker is currently working in the West

$$w_{it} \quad = \quad \alpha_i + \psi_{J(i,t)} + BX_{it} + \mathbb{I}_i^{(b_i=\text{East};\, r_i=\text{West})} + \epsilon_{it}, \tag{9}$$

A negative coefficient on this term would indicate that conditional on an individual's skill component and establishment, she receives a lower wage in the West than in the East. In the second part of Appendix C, we discuss how this additional term is identified from comparing an East and a West German worker moving between the same two establishments in the East and in the West. The coefficient on this variable is presented in row (4) of Table 2. We find that it is close to zero, and in fact slightly positive.

The comparative advantage coefficient is identified only out of a selected group of individuals: individuals that worked in both regions. This selection could bias our estimate. While this concern is a fundamental identification issue that cannot be overcome without exogenous migration shocks, we can provide some further supportive evidence using heterogeneity across age groups. We run specification (9) interacting the comparative advantage coefficient with a birth-cohort dummy for three groups of individuals: i) those born before 1965; ii) those born between 1965 and 1975; and iii) those born after 1975. The third group of individuals went to high-school and college mostly after the reunification, and we may therefore expect that their skills are on average valued relatively similarly by firms in the East and West. Under the, arguably strong, assumption that migrants from the three age groups are similarly selected on comparative advantage, we can then use group iii) as a control for selection. Table 15 in Appendix G shows that the two older birth cohorts have a small comparative disadvantage in working away from their home region relative to the young, of approximately 3%. Further, and importantly, in our data, more than 30% of East born workers have spent some time working in the West. Finally, the model we write in Section 4 provides a structural interpretation to specification (9).

Overall, we conclude that workers skills are mostly transferable across space and comparative advantage does not play a relevant role in explaining home bias, especially if compared to the large magnitude of the other channels.

3.6 Further Results for Interpretation and Robustness

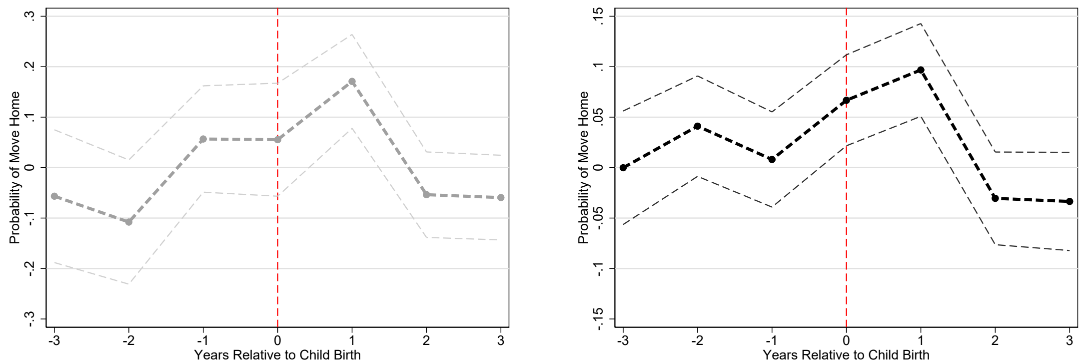
We will use the model to elucidate how the home bias is shaped by skills, preferences, and comparative advantages. Even without the model, however, we can shed some light on the sources of the attractiveness of the home region. First, we document that individuals are more likely to move back to their home region after the birth of a child, indicating that familial ties may play a role. Second, we show that East-born workers are more likely to move to counties that already contain a significant number of East-born individuals in the West. Finally, we show that workers' ties to their home region (East or West) go beyond simply their attachment to their federal state.

We begin by examining the role of child birth on workers' mobility, and exploit the fact that the

Figure 6: Child Birth Event Study

(a) East to West Return Move Probability

(b) West to East Return Move Probability



SOEP contains a variable which records whether individuals had a child. Using the old sample in the SOEP, we focus on the subsample of full-time workers that are currently employed in their non-native region and run

$$Migr_{it} = \alpha + \sum_{\tau=-3}^{3} \beta_\tau \mathbb{D}_\tau + \epsilon_{it}, \tag{10}$$

where $Migr_{it}$ is a dummy that is equal to one if the worker moves back to her home region, and $\mathbb{D}_\tau$ are dummies around a child birth event (at $\tau = 0$).[25] Figure 6a shows the estimated coefficients for East-to-West return moves of West-born workers, while Figure 6b presents the coefficients for West-to-East return moves of East-born workers. We find a significant spike of these return moves one year after the birth of a child. The finding suggests that familial ties may be important in explaining a worker's attachment to her home region.

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 a few million individuals fled to West Germany after having spent several years in the East to pre-empt 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, but focus on migration flows instead. Table 8 shows that those counties in the West that exogenously received more East-tied individuals before 1961 are also relatively more attrative for East-born individuals in 2009-2014. Specifically, columns (1) and (2) regress the gaps in the destination and origin fixed effects from regression (7) on the instrumented inflows of East-tied individuals.[26] Coefficients are normalized in terms of standard deviations. The results have the expected sign – larger inflows lead to stronger attractiveness of a county – and are large in magnitude

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

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

Table 8: 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	.29	$-$**.59***	.45	$-$**.56****
	(.40)	(.35)	(.30)	(.28)
Log Income p.c. 1989	$-.17$	.06	.05	$-.00$
	(.10)	(.09)	(.08)	(.07)
Distance to East	.02	$-.06$	.10	.01
	(.12)	(.11)	(.09)	(.08)
γ_d^W			**.55*****	
			(.05)	
δ_o^W				**.62*****
				(.04)
State FE	Y	Y	Y	Y
Observations	291	291	291	291

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

but 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 column (3) and (4) we replicate the same analysis using simply the county fixed effects for East-born and controlling for the ones of West-born. 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.

We finally study worker flows and wage changes across states rather than regions. If home bias is important, it should also affect workers' mobility across different federal states, and in fact it might be this attachment to a home state rather than a home region that is driving our findings. To show that home bias by region plays an important role, we first re-run the county-level distance regression (6), but add in three further terms for crossing a state border, leaving an origin county in the home state, and moving to a destination county in the home state, respectively. These possibilities are captured in the set $\mathbb{M} = \{S(o) \neq S(d), S(o) = b, S(d) = b\}$. We thus run:

$$\log s_{o,d}^b = \delta_o + \gamma_d + \mu^b + \sum_{x \in \mathbb{X}} \phi_x D_{x,o,d} + \sum_{k \in \mathbb{K}} \beta_k \mathbb{I}_{it}^k + \sum_{m \in \mathbb{M}} \gamma_l \mathbb{I}_{it}^l + \epsilon_{o,d}^b, \tag{11}$$

where we determine the home state analogously to the home region. Column (1) of Table 9 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 strong 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

Table 9: States Versus Regions

	(1)		(2)
	Flows		Wages
$\mathbb{I}^{(R(o)\neq R(d))}$	$-$**.1527*****	$d_{it}^{EW,W,m}$	**.1942*****
	(.0072)		(.0268)
$\mathbb{I}^{(R(o)=b)}$	$-$**.7955*****	$d_{it}^{WE,W,m}$	**.1033*****
	(.0782)		(.0313)
$\mathbb{I}^{(R(d)=b)}$	**0.5000*****	$d_{it}^{EW,E,m}$	**.2320*****
	(.0769)		(.0168)
		$d_{it}^{WE,E,m}$	.0335
			(.0204)
$\mathbb{I}^{(S(o)\neq S(d))}$	$-$**.2037*****	$\mathbb{I}^{(S(o)\neq S(d))}$	**.0325*****
	(.0083)		(.0105)
$\mathbb{I}^{(S(o)=b)}$	$-$**2.6677*****	$\mathbb{I}^{(S(o)=b)}$	**.1070*****
	(.0060)		(.0135)
$\mathbb{I}^{(S(d)=b)}$	**0.7499*****	$\mathbb{I}^{(S(d)=b)}$	$-$**.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.

or region bias.

We similarly add the three dummies in $\mathbb{M}$ to the wage gain regression (8). Column (2) of Table 9 shows that there is still significant home bias for the home region, in addition to a bias towards the state.

4 A Multi-Region Model of a Frictional Labor Market

The data suggest that the home bias might be a relevant factor in determining the allocation of workers across regions and firms, and thus the wage gaps by region and birth-place. However, the empirical analysis falls short on several dimensions. For example, it does not allow us to quantify the importance of home bias, or to unpack it into its different components. To make progress along these dimensions, we develop a model with three objectives. First, the model is necessary for proper inference, and specifically to map the observables differences between East- and West-born workers into interpretable primitive parameters. Second, the model allows us to compute the fraction of the observed wage gap between East- and West-born that can be generated by the home bias alone, once we discipline its strength using the empirical moments of Section 3. Third, the model provides a laboratory to perform counterfactual analysis in general equilibrium, taking into account firms' endogenous response to changes in the labor supply.

We these three aims in mind, we develop a model of frictional labor reallocation. The nature of our data calls for two types of reallocation: (i) spatial movements across East and West Germany; (ii) reallocation within each region across heterogeneous firms. Including within-region labor reallocation across firms is necessary to use the wage gains of movers to recover regional preferences. 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.

We build on the work of Burdett and Mortensen (1998) and of more recent empirical applications, such as Moser and Engbom (2017). 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 distorts movement of workers between regions, closer to the work in spatial macro and trade (e.g., Caliendo, Opromolla, Parro, and Sforza (2017)). Importantly, and departing from previous literature, spatial frictions are not generated in our setting by mobility costs, from which we abstract, but rather by the workers' home bias. In fact, in our model, only the worker's birth-place, rather than his current location, will affect his continuation value. These assumptions preserve tractability, and permit us to build the first, to our knowledge, general equilibrium model that encompasses spatial and reallocation frictions within a unified framework. Moreover, the absence of distance within the model is consistent with our empirical specifications, which controlled for distance. We will further discuss the role of these assumptions in Section 5.2.

4.1 Model Setup

We first provide a broad overview of the environment, then we study the problem of workers and firms, and last we discuss how the labor market clears.

Environment. Let time be continuous. There are $\mathbb{J}$ regions in an economy which is inhabited by a continuum of mass 1 of workers of types $i \in \mathbb{I}$, where $\mathbb{I} = \{1, .., I\}$. We denote the mass of workers of type i by $\bar{D}^i$, where $\sum_{i \in \mathbb{I}} \bar{D}^i = 1$. The workers differ in both their ability and in their taste for being in a given region. Specifically, a worker of type i produces θ^i_j units of output per time unit in region j, where we use superscripts for worker types and subscripts for regions. If this worker is employed at wage rate w per efficiency unit, he earns an income of $w\theta^i_j$. Furthermore, worker i has a preference parameter of τ^i_j for being in region j. Assuming linear utility as is standard in models following Burdett and Mortensen (1998), worker i's utility from receiving wage rate w in region j is $u^i_j = w\theta^i_j\tau^i_j$.

Workers operate in a frictional labor market and can either be employed or unemployed. A worker of type i faces an arrival rate of vacancy offers from region j of $\varphi_j^i \lambda_j$, where λ_j is the endogenous arrival rate of offers from region j, determined below, and φ_j^i is an exogenous wedge, which we normalize to satisfy $\sum_{i \in \mathbb{I}} \varphi_j^i \bar{D}^i = 1$. This wedge captures for example that offers from East German firms may be more likely to reach workers born in East Germany due to reliance on social networks and referreal for offers. There are two types of job offers: a fraction $\left(1 - \chi^i\right)$ are job offers that workers can decide to accept or not, as is standard, and a fraction χ^i are offers that the worker cannot refuse, informally called *Godfather shocks* in the literature. Workers always have the possibility to separate into unemployment if an offer received gives utility below the reservation wage. While these shocks are not needed for our theoretical discussion, the additional flexibility will be useful to match the data to generate a sufficiently high number of firm-to-firm moves that generate a wage decrease. We will refer to these offers as churning.

We assume that the arrival rate of offers does not depend on the region in which the worker is currently located, but only on the worker type. Workers draw offers from the endogenous distributions of wages F_j in all regions j, and must decide whether to accept an offer as soon as it is received. They separate into unemployment at rate δ^i irrespective of where they are working, and receive a utility flow equal to b^i when unemployed. The assumptions that the arrival rate of offers, δ^i, and b^i depend only on worker's type implies, as we will show and discuss below, that workers accept across-region wage offers only based on present utility flows and not on different continuation values. We will discuss empirical evidence supporting these assumptions when we take the model to the data in Section 5.2.

On the firm side, there is a continuum of firms exogenously assigned to regions $j \in \mathbb{J}$, where Γ_j is the mass of firms in region j and $\sum_{j \in \mathbb{J}} \Gamma_j = 1$. Within each region, firms are distributed over productivity p according to density function $\frac{\gamma_j(p)}{\Gamma_j}$ with support on the positive real line. The support of firms with positive mass is a region-specific closed set $[\underline{p}_j, \bar{p}_j] \subseteq \mathbb{R}^+$. Firms produce output from each vacancy with the production function $Y_j = p \sum_{i \in \mathbb{I}} \theta_j^i l_j^i$, where $\sum_{i \in \mathbb{I}} \theta_j^i l_j^i$ is the number of efficiency units of labor used by one vacancy of the firm.

Each firm p in region j decides how many vacancies $v_j\left(p\right)$ to post, subject to a vacancy cost $c_j\left(v\right)$, and what wage rate $w_j(p)$ to offer. Each vacancy meets workers at a rate that we normalize, without loss of generality, to one. 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 heterogenous types, see for example Moser and Engbom (2017), 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. All agents discount future income at rate r.

We next turn to the problems of workers and firms.

Workers Workers randomly receive offers from firms, and accept an offer if it provides higher expected value than the current one. As well known, this class of models yields a recursive representation.

The expected discounted lifetime utility of an unemployed worker of type i is the solution to

$$rU^{i} = b^{i}+\sum_{x\in\mathbb{J}}\varphi_{x}^{i}\lambda_{x}\left[\int\max\left\{U^{i},W_{x}^{i}\left(\tilde{w}\right)\right\}dF_{x}\left(\tilde{w}\right)-U^{i}\right], \tag{12}$$

where we denote by $W_{j}^{i}\left(w\right)$ the value of an employed worker i earning wage w in region j. The value of an unemployed worker of type i consists of the worker's flow benefit plus the expected value from finding a job, which is only accepted if this value exceeds the value from continuing search. Given the assumptions, the value of unemployment only depends on worker's type i, and not on last region of employment.

The value of an employed worker i earning wage w in region j solves

$$rW_{j}^{i}\left(w\right) = w\theta_{j}^{i}\tau_{j}^{i}+\sum_{x\in\mathbb{J}}\varphi_{x}^{i}\lambda_{x}\Bigg[\left(1-\chi^{i}\right)\int\max\left\{W_{j}^{i}\left(w\right),W_{x}^{i}\left(\tilde{w}\right)\right\}dF_{x}\left(\tilde{w}\right) \tag{13}$$

$$+\chi^{i}\int\max\left\{U^{i},W_{x}^{i}\left(\tilde{w}\right)\right)\right\}dF_{x}\left(\tilde{w}\right)-W_{j}^{i}\left(w\right)\Bigg]+\delta^{i}\left[U^{i}-W_{j}^{i}\left(w\right)\right]. \tag{14}$$

Under our assumptions, the value of an employed worker, and thus his decisions, only depend on the flow utility received by an offer and on his type and not on the region they are currently in. Lemma 1 summarizes this result.

Lemma 1. *For any type i and region j, the value function is given by*

$$W_{j}^{i}\left(w\right) = W^{i}\left(u\right)$$

where u is flow utility and

$$W^{i}\left(u\right) = u+\sum_{x\in\mathbb{J}}\varphi_{x}^{i}\lambda_{x}\Bigg[\left(1-\chi^{i}\right)\int\max\left\{W^{i}\left(u\right),W^{i}\left(\tilde{u}\right)\right\}dF_{x}\left(\frac{\tilde{u}}{\theta_{x}^{i}\tau_{x}^{i}}\right)+.$$

$$\chi^{i}\int\max\left\{U^{i},W^{i}\left(\tilde{u}\right)\right\}dF_{x}\left(\frac{\tilde{u}}{\theta_{x}^{i}\tau_{x}^{i}}\right)-W^{i}\left(u\right)\Bigg]+\delta^{i}\left[U^{i}-W^{i}\left(u\right)\right].$$

Further, a worker i employed at wage w in region j accepts an offer w' from region x if and only if it provides a weakly higher flow utility, that is if and only if

$$w'\theta_{x}^{i}\tau_{x}^{i} \geq w\theta_{j}^{i}\tau_{j}^{i}; \tag{15}$$

and while there exist a reservation utility $R^{i}=b^{i}$ such that

$$W^{i}(R^{i}) = U^{i},$$

the reservation wage is region specific and equal to

$$\hat{w}_j^i \quad = \quad \frac{b^i}{\tau_x^i \theta_x^i}. \tag{16}$$

Proof. See Appendix. □

Equation (15) shows that workers move from low utility to high utility jobs when the opportunity arises. For example, they may move to a firm that pays a lower wage per efficiency unit if they are moving to a region for which they have a stronger comparative advantage or preference. These type of moves would result in an increase in the worker's overall income but in a decline of the worker's wage rate. Equation (15) together with equation (16), shows that workers might prefer unemployment to working in a region for which they have low preference or shills.

Firms. Since the production function is linear, the firm-level problem of posting vacancies and choosing wages can be solved separately. Following the literature (e.g., Burdett and Mortensen (1998)), we focus on steady state: employers choose the wage rate that maximizes their steady state profits for each vacancy, which are

$$\pi_j(p) = \max_w (p-w) \sum_{i \in \mathbb{I}} \theta_j^i l_j^i(w). \tag{17}$$

The wage choice is determined by a trade-off between profit margins and firm size. On the one hand, 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, which introduces a non-convexity, since the labor function $l_j^i(w)$ may be discontinous, as we will show.

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

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

where $\pi_j(p)$ are the maximized profits per vacancy from (17). The size of a firm p in region j is therefore given by $l_j(w_j(p))v_j(p)$. Moreover, the vacancy posting policy from the firm problem gives us the endogenous arrival rate of offers from each region

$$\lambda_j \quad = \quad \int_{\underline{p}_j}^{\bar{p}_j} v_j(p) \gamma_j(p) \, dp, \tag{18}$$

and the wage policy gives us the endogenous distribution of offers

$$F_j(w_j(p)) = \frac{1}{\lambda_j}\int_{\underline{p}_j}^{p} v_j(p)\gamma_j(p)\,dp. \tag{19}$$

Allowing for 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.

Market Clearing. To close the model, we need to describe how the distribution of workers to firms is determined. Lemma 1 shows that distribution of workers over their current flow utility is to sufficient to compute the probability that a wage posted in any given region is accepted. We define $\Upsilon^i(u) \equiv D^i(u)/\bar{D}^i$ to be the share of workers of type i that need to receive at least utility u in order to accept a new offer over their current one, where $\Upsilon^i(u)$ is the cumulative distribution function (CDF) over these workers' reservation utility. Since no worker accepts a wage providing lower utility than unemployment, the support of D^i is bounded below by b^i. The law of motion of $D^i(u)$, for $u \geq b^i$, is

$$\dot{D}^i(u) = \delta^i\left(\bar{D}^i - D^i(u)\right) - \left(\bar{\lambda}^i - \left(1-\chi^i\right)\hat{\lambda}^i(u)\right)D^i(u) + \chi^i\hat{\lambda}^i(u)\bar{D}^i, \tag{20}$$

where dots represent time derivatives, and we define $\bar{\lambda}^i \equiv \sum_{x\in\mathbb{J}}\varphi^i_x\lambda_x$ to be the total rate of offers received by workers i, and $\hat{\lambda}^i(u) \equiv \sum_{x\in\mathbb{J}}\varphi^i_x\lambda_x F_x(u/(\theta^i_x\tau^i_x))$ to be the total rate of offers received that give utility below u. The first term in equation (20) captures worker flows from jobs offering a higher utility than the current utility u into unemployment, which increases $D^i(u)$. The second term represents outflows of workers either due to churning – given by $\chi^i\hat{\lambda}^i(u)$ – or to jobs offering a higher utility than u.[27] The third term represents inflows of workers to jobs offering lower utility than u due to churning.

In steady state, $\dot{D}^i(u) = 0$, and we have

$$D^i(u) = \frac{\delta^i + \chi^i\hat{\lambda}^i(u)}{\delta^i + \bar{\lambda}^i - \left(1-\chi^i\right)\hat{\lambda}^i(u)}\bar{D}^i, \tag{21}$$

if $u \geq b$, and $D^i(u) = 0$ for $u < b$. The unemployment rate of workers of type i is $D^i(b)/\bar{D}^i$.

Denote by $l^i_j(w)$ the measure of workers of type i employed at one vacancy posted in region j offering wage w. For $w\theta^i_j\tau^i_j \geq b^i$ the law of motion of $l^i_j(w)$ is given by

$$\dot{l}^i_j(w) = \chi^i\varphi^i_j\bar{D}^i + \left(1-\chi^i\right)\varphi^i_j D^i\left(\theta^i_j\tau^i_j w\right) - q^i\left(\theta^i_j\tau^i_j w\right)l^i_j(w),$$

where the first term represents worker inflows due to churning, and the second term are inflows through normal offers, which are accepted with probability $\varphi^i_j D^i\left(\theta^i_j\tau^i_j w\right)$. Outflows are equal to the mass of

[27] Note that $\bar{\lambda}^i - \hat{\lambda}^i(u)$ is equal to the total rate of accepted offers, since it is equal to the offers received minus those that provide utility below u, hence would not be accepted.

workers $l_j^i(w)$ multiplied by the rate at which workers separate into unemployment due to churning or moving to firms that provide higher utility

$$q^i(u) = \delta^i + \bar{\lambda}^i - \left(1-\chi^i\right)\hat{\lambda}^i(u). \tag{22}$$

Firms that offer a higher utility flow u are characterized by lower outflows, since workers are less likely to be poached by other firms. In steady state, using expression (21) for $D^i(u)$, we obtain a measure of workers per vacancy of

$$l_j^i(w) \quad = \quad \frac{\left(\delta^i + \chi^i\hat{\lambda}^i\left(\theta_j^i\tau_j^i w\right) + q^i\left(\theta_j^i\tau_j^i w\right)\frac{\chi^i}{(1-\chi^i)}\right)\left(1-\chi^i\right)\varphi_j^i\bar{D}^i}{\left[q^i\left(\theta_j^i\tau_j^i w\right)\right]^2} \tag{23}$$

if $\theta_j^i\tau_j^i w \geq b^i$, and zero otherwise.

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

Definition 1: Stationary Equilibrium. *A stationary equilibrium 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* $\left\{q_j^i(p)\right\}_{j\in\mathbb{J},i\in\mathbb{I}}$*, and worker utility distributions* $\left\{D^i(u)\right\}_{i\in\mathbb{I}}$ *such that*

1. *workers accept offers that provide higher utility, 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 (18) and (19);*

4. *firm sizes and worker distributions satisfy the stationary equations (21) and (23), where* $q_j^i(p) = q^i\left(\theta_j^i\tau_j^i w_j(p)\right)$.

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, and comparative advantages. In order to understand the structure of our model, it is useful to compare it with the benchmark Burdett-Mortensen model, which is a special case of our model when all worker heterogeneity is shut down and there is only one region. In this 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. We emphasize two key aspects of this solution. First, the 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. Second, the wage policy must be continuous. A discontinuity cannot be optimal, since a discrete jump in wage cannot lead to a discret jump in firm size, the reason being that firm size is purely determined by the ranking of wage offers and not by their level. In our setting these insights generalize, but need to be refined. Due to the presence of several types of workers and regions, discountinuities in the wage policy may arise. In fact, in our setting the size of the firm can increase discountinously if the wage increase is sufficient to attract workers of an additional type. More broadly, in our setting, within a given (i, j) pair only the ranking of wage matters for firm size, as in the benchmark model, but across regions and worker types also the level of the wage is relevant. As a result, we can show that the equilibrium is given by a set of piece-wise differential equations and endogenous boundary conditions for optimality.

Proposition 1. *The solution of the stationary equilibrium solves a set of J plus $J \times I$ differential equations*

$$\begin{aligned}\frac{\partial w_j(p)}{\partial p} &= H_j\left(\left\{q_j^i(p)\right\}_{j\in J, i\in I}, \left\{w_j(p)\right\}_{j\in J}\right)\\ \frac{\partial q_j^i(p)}{\partial p} &= K_j^i\left(\left\{q_j^i(p)\right\}_{j\in J, i\in I}, \left\{w_j(p)\right\}_{j\in J}\right)\end{aligned}$$

together with $J \times I$ boundary conditions for $q_j^i(\bar{p}_j)$, $J \times I$ cutoffs for firm types that have the lowest productivity to hire workers of type i in region j, defined by $\hat{p}_j^i = \min p_j$ such that $w_j(p_j) \geq R^i$, and $J \times I$ boundary conditions for $w_j\left(\hat{p}_j^i\right)$.

Proof. The proof formalizes the previous discussion on the economic forces present in our model, and provides the analytical expressions for the differential equations, which can be efficiently solved for any generic J and I. The formal proof for the general case is left to the Appendix D.1. Here, we highlight the main steps for a simple symmetric case, with two identical regions, two worker types, each biased towards one region, and no churning – i.e. $\chi^i = 0$.

Consider the parametrization $I = J = 2$, $b^1 = b^2 = b$, $\delta^1 = \delta^2 = \delta$, $\bar{D}^1 = \bar{D}^2 = \frac{1}{2}$, $\Gamma_1(p) = \Gamma_2(p) = \Gamma(p)$ with support on $p \in \left[\underline{p}, \bar{p}\right]$, where $\underline{p} \in \left[b, \frac{b}{\tau\theta}\right)$, $c_1(v) = c_2(v) = c(v)$, and

$$\theta_j^i = \begin{cases}1 & \text{if } i = j\\ \theta < 1 & \text{if } i \neq j\end{cases} \qquad \varphi_j^i = \begin{cases}1 & \text{if } i = j\\ \varphi < 1 & \text{if } i \neq j\end{cases} \qquad \tau_j^i = \begin{cases}1 & \text{if } i = j\\ \tau < 1 & \text{if } i \neq j\end{cases}.$$

We focus on region 1. Due to symmetry, the problem for region 2 is identical.

We need to find the differential equations for wages and the separation rates together with their boundary conditions. We begin with wages. Taking the first order conditions from the wage posting problem (17) for a firm p in region 1 yields

$$\frac{\left(p-w_1\left(p\right)\right)\left(\frac{\partial l_1^1\left(w_1\left(p\right)\right)}{\partial w}+\theta\frac{\partial l_1^2\left(w_1\left(p\right)\right)}{\partial w}\right)}{l_1^1\left(w_1\left(p\right)\right)+\theta l_1^2\left(w_1\left(p\right)\right)} \quad = \quad 1, \tag{24}$$

where $l_1^1\left(w_1\left(p\right)\right)=\frac{\frac{1}{2}\delta}{\left[q^1\left(w_1\left(p\right)\right)\right]^2}$ if $w_1\left(p\right)>b$ and 0 otherwise, and $l_1^2\left(w_1\left(p\right)\right)=\frac{\frac{1}{2}\varphi\delta}{\left[q^2\left(\tau\theta w_1\left(p\right)\right)\right]^2}$ if $w_1\left(p\right)>\frac{b}{\tau\theta}$ and 0 otherwise. Since $\underline{p}<\frac{b}{\tau\theta}$ by assumption, the wage paid by the lowest productivity firm satisfies $w_1\left(\underline{p}\right)<\frac{b}{\tau\theta}$. Moreover, by the usual argument of Burdett and Mortensen model, we have that the first boundary condition is $w_1\left(\underline{p}\right)=b$. Therefore, the lowest productivity firm in region 1 only hires workers of type 1.

We next solve for the lowest productivity firm that finds it optimal to post a wage high enough to attract workers of type 2. We denote this firm by $\hat{p}_1^2$. Consider the per vacancy profits of a firm p when it hires only workers of type 1 – $\pi_1^1\left(p\right)$ – and when it hires both types of workers – $\pi_1^2\left(p\right)$. These profits are given by

$$\begin{aligned}\pi_1^1\left(p\right) &= \max_{w\geq b}\left(p-w\right)l_1^1\left(w\right)\\ \pi_1^2\left(p\right) &= \max_{w\geq\frac{b}{\tau\theta}}\left(p-w\right)\left(l_1^1\left(w\right)+l_1^2\left(w\right)\right).\end{aligned}$$

Since both π_1^1 and π_1^2 are continous, the firm $\hat{p}_1^2$ must be indifferent between hiring only workers of type 1 and hiring both types of workers, i.e.,

$$\pi_1^1\left(\hat{p}_1^2\right)=\pi_1^2\left(\hat{p}_1^2\right).$$

Figure (8a) plots the wage function $w_1(p)$ over the domain of productivity $[\underline{p},\bar{p}]$. In proximity of $\hat{p}_1^2$ the wage equation $w_1\left(p\right)$ is discontinous. Intuitively, it cannot be optimal for any firm to post a wage of just below $\frac{b}{\tau\theta}$, since in that case an infinitesimal wage increase to $\frac{b}{\tau\theta}$ would lead to a discrete jump in firm size by attracting the entire mass of unemployed workers of type 2, thus increasing profits. Firm $\hat{p}_1^2$ is indifferent between posting a lower wage and hiring only workers of type 1, or paying a premium to discretely increase the size of the firm by hiring also workers of type 2. The second boundary condition is thus given by

$$w_1\left(\hat{p}_1^2\right)=\arg\max_{w\geq\frac{b}{\tau\theta}}\left(\hat{p}_1^2-w\right)\left(l_1^1\left(w\right)+l_1^2\left(w\right)\right).$$

We next differentiate equation (24) with respect to p, and use equation (23) to get the step-wise differential equation for $w_1(p)$[28]

$$\frac{\partial w_1(p)}{\partial p} = -(p - w_1(p)) \left(\frac{\frac{\delta\left(\frac{\partial q_1^1(p)}{\partial p}\right)}{\left[q_1^1(p)\right]^3} + \mathcal{I}\left\{p \geq \hat{p}_1^2\right\} \frac{\varphi\theta\delta\left(\frac{\partial q_1^2(p)}{\partial p}\right)}{\left[q_1^2(p)\right]^3}}{\frac{\delta}{\left[q_1^1(p)\right]^2} + \mathcal{I}\left\{p \geq \hat{p}_1^2\right\} \frac{\varphi\theta\delta}{\left[q_1^2(p)\right]^2}} \right) \tag{25}$$

where $\mathcal{I}\left(p \geq \hat{p}_1^2\right)$ is an indicator function equal to one for $p \geq \hat{p}_1^2$. This completes the description of the differential equation for wages.

We next show how to derive the differential equations for the separation rates. From equation (22), notice that to compute $q_1^2(p)$, and thus its derivative, we need to compute the share of offers from regions 1 and 2 that the different types of workers are willing to accept. Consider first offers from region 1. Irrespective of her type, within the same region a worker employed at wage $w_1(p)$ is willing to accept all offers that pay $w > w_1(p)$. For moves to region 2, workers of type 1 are willing to accept only offers that pay $w > \frac{w_1(p)}{\tau\theta}$, while workers of type 2 are willing to accept all offers that pay $w > \tau\theta w_1(p)$. We define the marginal productivity types $\psi_{12}^1(w_1(p))$ and $\psi_{12}^2(w_1(p))$ which make workers exactly different between moving from firm p offering wage $w_1(p)$ in region 1 to region 2 as $w_2\left(\psi_{12}^1(w_1(p))\right) = \frac{w_1(p)}{\tau\theta}$ and $w_2\left(\psi_{12}^2(w_1(p))\right) = \tau\theta w_1(p)$. Notice that $\psi_{12}^1(w_1(p))$ and $\psi_{12}^2(w_1(p))$ may not exist for some p. Specifically, for $p < \hat{p}_1^2$, workers of type 2 are unwilling to move to region 1 since $w_2\left(\underline{p}\right) > \tau\theta w_1(p)$, and thus $\psi_{12}^2(w_1(p))$ does not exist for such p. Similarly, we define $\breve{p}_{12}^1$ such that $\frac{w_1(\breve{p}_{12}^1)}{\tau\theta} = w_2(\bar{p})$, that is, no firm in region 2 posts a wage that is sufficiently high to poach workers of type 1 that are employed in firms with productivity above $\breve{p}_{12}^1$. Then $\psi_{12}^1(w_1(p))$ does not exist for $p > \breve{p}_{12}^1$.

Differentiating equation (22) with respect to p, and using the offer distribution (19), we get the desired differential equations for the separation rates

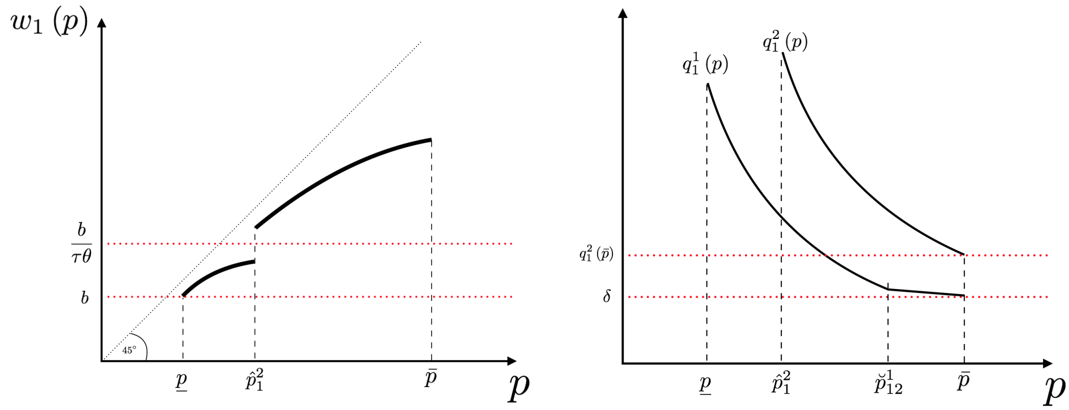
$$\begin{aligned}
\frac{\partial q_1^1(p)}{\partial p} &= -v_1(w_1(p))\,\gamma_1(w_1(p)) - \mathcal{I}\left(p \leq \breve{p}_{12}^1\right)\left(\frac{\partial \psi_{12}^1(w_1(p))}{\partial p}\right) v_2\left(\psi_{12}^1(w_1(p))\right)\gamma_2\left(\psi_{12}^1(w_1(p))\right)\\
\frac{\partial q_1^2(p)}{\partial p} &= -v_1(w_1(p))\,\gamma_1(w_1(p)) - \mathcal{I}\left(p \geq \hat{p}_1^2\right)\left(\frac{\partial \psi_{12}^2(w_1(p))}{\partial p}\right) v_2\left(\psi_{12}^2(w_1(p))\right)\gamma_2\left(\psi_{12}^2(w_1(p))\right),
\end{aligned}$$

where $\mathcal{I}\left(p < \breve{p}_{12}^1\right)$ and $\mathcal{I}\left(p \geq \hat{p}_1^2\right)$ are indicator functions.

Figure (8b) visualizes these separation rate functions. Their boundary conditions are determined as follows. The highest productivity firm in region 1 will only lose workers of type 1 to unemployment, and therefore the first boundary condition is $q_1^1(p) = \delta$. The function $q_1^1(p)$ has a kink at $p = \breve{p}_{12}^1$, since for $p > \breve{p}_{12}^1$ workers of type 1 only quit for higher productivity firms within the same region. The

[28]Readers familiar with the Burdett and Mortensen model should recognize that in the presence of only one worker type, equation (25) simplifies to the standard differential equation for wage.

Figure 7: Equilibrium in Region 1



(a) Wage Function: $w_1(p)$ (b) Separation Rates: $q_1^1(p)$ and $q_1^2(p)$

boundary condition for $q_1^2(p)$ is

$$q_1^2(\bar{p}) = \delta + \lambda_2 (1 - F_2 (\tau\theta w_1 (\bar{p}))) = \delta + \lambda_2 \int_{\breve{p}_{12}^2}^{\bar{p}} v_2(z)\gamma_2(z)\,dz.$$

Firms in region 2 can poach workers of type 2 even from the highest productivity firm in region 1, given these workers' preferences.

We have completely characterized the system of differential equations and boundary conditions that pin down the equilibrium wage function and the separation rates in region 1. The solution for region 2 is identical. The proof for the general case follows a similar path, but needs to consider all the possible shapes of the wage function; that is, the fact that the wage function may have any number of discountinuities between 0 and $I-1$. Moreover, it needs to take into consideration the fact that in some regions some workers type may not be hired even from the highest productivity firms. □

4.3 Spatial and Reallocation Frictions

Our model allows us to distinguish explicitly between two types of frictions: *reallocation frictions*, which, as in the class of models along the lines of Burdett and Mortensen (1998), prevent reallocation of workers to more productive firms; and *spatial frictions*, which distort the allocation between regions due to home bias. Taking into account both types of frictions is necessary for our quantitative analysis in Section 5 for two reasons. First, the wage gains when workers move across regions, which will be used to estimate the preference component of spatial frictions, depend on the distribution of job offers, which in turn depend on the reallocation frictions in the economy. Second, in our counterfactual exercise the equilibrium response of firms' job offers to changes in spatial frictions is dependent on the reallocation frictions in the economy. We next formally define each type of friction.

Our definition of reallocation frictions follows closely the previous literature (e.g., Mortensen (2005)), where the ratio of the job destruction (or separation) parameter, δ, to the contact (or offer) rate per worker, λ, has become known in the literature as the "market friction parameter" . We generalize this definition to our setting, where both the offer and separation rates are endogenous and firm/region specific.[29]

Definition 2: Reallocation Frictions. *The reallocation friction for a firm p in region j is*

$$\phi_j(p) \equiv \frac{\delta_j(p)}{\lambda_j(p)}$$

where $\lambda_j(p) = \upsilon_j(p)$ and $\delta_j(p) \equiv \frac{\sum_{i\in\mathbb{I}} \delta^i l^i_j(p)}{\sum_{i\in\mathbb{I}} l^i_j(p)}$. The average reallocation friction in region j is then

$$\phi_j \equiv \frac{\delta_j}{\lambda_j}$$

where $\lambda_j = \int \lambda_j(p)\gamma_j(p)\,dp$ and $\delta_j = \int \delta_j(p)\gamma_j(p)\,dp$.

For the spatial frictions, the previous literature does not provide a lead, and hence we devise our own definition.

Definition 3: Spatial Biases and Frictions. *The spatial bias for workers of type i in favor of region j with respect to j' is*[30]

$$\Lambda^i(j,j') \equiv \underbrace{\log\varphi^i_j - \log\varphi^i_{j'}}_{\textit{Offer Bias}} + \underbrace{\log\tau^i_j - \log\tau^i_{j'}}_{\textit{Taste Bias}} + \underbrace{\log\theta^i_j - \log\theta^i_{j'}}_{\textit{Skill Bias}}.$$

The spatial friction for workers i is then

$$\Upsilon^i \equiv \mathit{Var}\left[\Lambda^i(j,j')\right]$$

The spatial friction for the overall economy is

$$\Upsilon \equiv \sum D^i \Upsilon^i.$$

The spatial bias captures how attracted a given worker type is to a specific region only as a consequence

[29]The offer rate is endogenous since it depends on the number of posted vacancies. The separation is endogenous since it depends on the relative share of workers of each type.

[30]Notice that in the knife-edge case when $\varphi^i_j = \varphi^i_{j'} = 0$ – or similarly for τ and θ – we will have that the bias is equal to $-\infty + \infty$, hence undefined. In that specific case, we pin down the "undefined" answer by assigning the relevant spatial bias to 0.

of the worker-specific characteristics. Consider two hypothetical regions j' and j, in which firms post identical vacancy and wage distributions. The value of $\Lambda^i(j, j')$ then captures the percentage difference in the expected value of offers from j' relative to j. By construction, the average spatial bias across all possible region pairs – $\frac{1}{J^2}\sum_{j\in\mathbb{J}}\sum_{j'\in\mathbb{J}}\Lambda^i(j, j')$ – is equal to zero. Therefore, the larger are the spatial biases in absolute value, the more workers are attracted to some regions relative to others. It therefore becomes natural to define the spatial frictions as a norm of the spatial bias vector. Lacking specific guidance, we choose the variance for simplicity. Notice that if, for a given worker type, all regions are identical, then the spatial friction would be zero for this worker type. The spatial friction for the whole economy is simply the weighted average across all worker types.

To provide some intuition for how spatial frictions affect the equilibrium, we solve and discuss three cases of our economy. Figure 8 plots, for each case, a computation of the solution of a two-regions, two-types economy.[31] We interpret the two regions as East and West, and the two types as East- and West-born workers. Each column corresponds to one of three cases we study. The first row shows wage functions, the second one employment of East born workers in each region, the third one employment of West born workers, and the fourth one the relationship between wage and size.

The first column depicts the case where the spatial bias between regions is infinite, and therefore there is no mobility across regions. The parameters in East and West are the same, except that the productivity and the cost of vacancy posting in the East are shifted a region specific parameter, which can be interpreted as aggregate productivity. We also scale workers' unemployment value b^i by this parameter. In Appendix E, we provide a full analytic characterization for this case, and focus on the intuition here. Rows two and three show that no workers are employed in their non-native region. The fourth row shows that firms in East Germany are larger than firms in the West posting the same real wage. Intuitively, with spatial frictions, firms in the low productivity East Germany are shielded from competition from higher productivity West firms, which allows them to grow larger without needing to post a higher wage. This outcome, as we show in Section 5.4, is consistent with the data. However, the full separation case clearly misses the extensive reallocation of workers across regions.

The second column presents the case without spatial frictions and hence full mobility between regions. East and West Germany only differ in their aggregate productivity, and East- and West-Germans only in their value of unemployment. Again, in Appendix E, we provide a full analytic characterization for this case, and focus on the intuition here. While this version of the model generates a lot of mobility across regions, workers' birth location does not affect their likelihood to work in a given region, at odds with the data. The figure also highlights that spatial wage gaps alone are not sufficient to identify spatial frictions. Even in the absence of any spatial frictions wages can be lower in East Germany due to reallocation frictions, which keep some workers at the lower productivity firms in the East. Finally, the figure highlights one property of the solution that is unique to our framework. Since we have assumed $b^W > b^E$, the lowest productivity firms, in either region, only hire East born workers. Moreover, there exists a marginal firm that is the first one to post a wage sufficiently high to

[31] For the two cases with zero or infinite spatial bias, the model can be solved analytically. See Appendix E.

hire also West workers. At this marginal firm, the wage jumps discountinously.[32]

Finally, the third column presents the case of two partially integrated labor markets and two worker types, each biased towards one region. This is the case that most closely resembles Germany. We emphasize several points. First, in both regions, the least productive firms only hire workers from their own region, since their wages are too low to attract the other type of workers. In West Germany, these firms pay a higher wage than in the East, since unemployment benefits for West German workers are higher. Only the very best East German firms are able to attract West German workers, while East German workers are willing to move even to relatively unproductive firms in the West. This prediction of the model resembles the empirical results shown in Section 3. Finally, firms in the East are relatively larger than those in the West since they face a slacker labor market, although the gap is smaller than in the case with no mobility. Intuitively, since aggregate productivity is lower in the East, a firm posting a given wage level must be at a higher position in the East German productivity distribution than in the West, which allows it to hire more workers.

5 Quantitative Analysis

We now use the model in the context of the German labor market. We first discuss our strategy to bring the model to the data and explain how it helps us to identify the home bias parameters. We then estimate the model and show its fit. Finally, we use the estimated model to quantify the role of home bias and run counterfactuals.

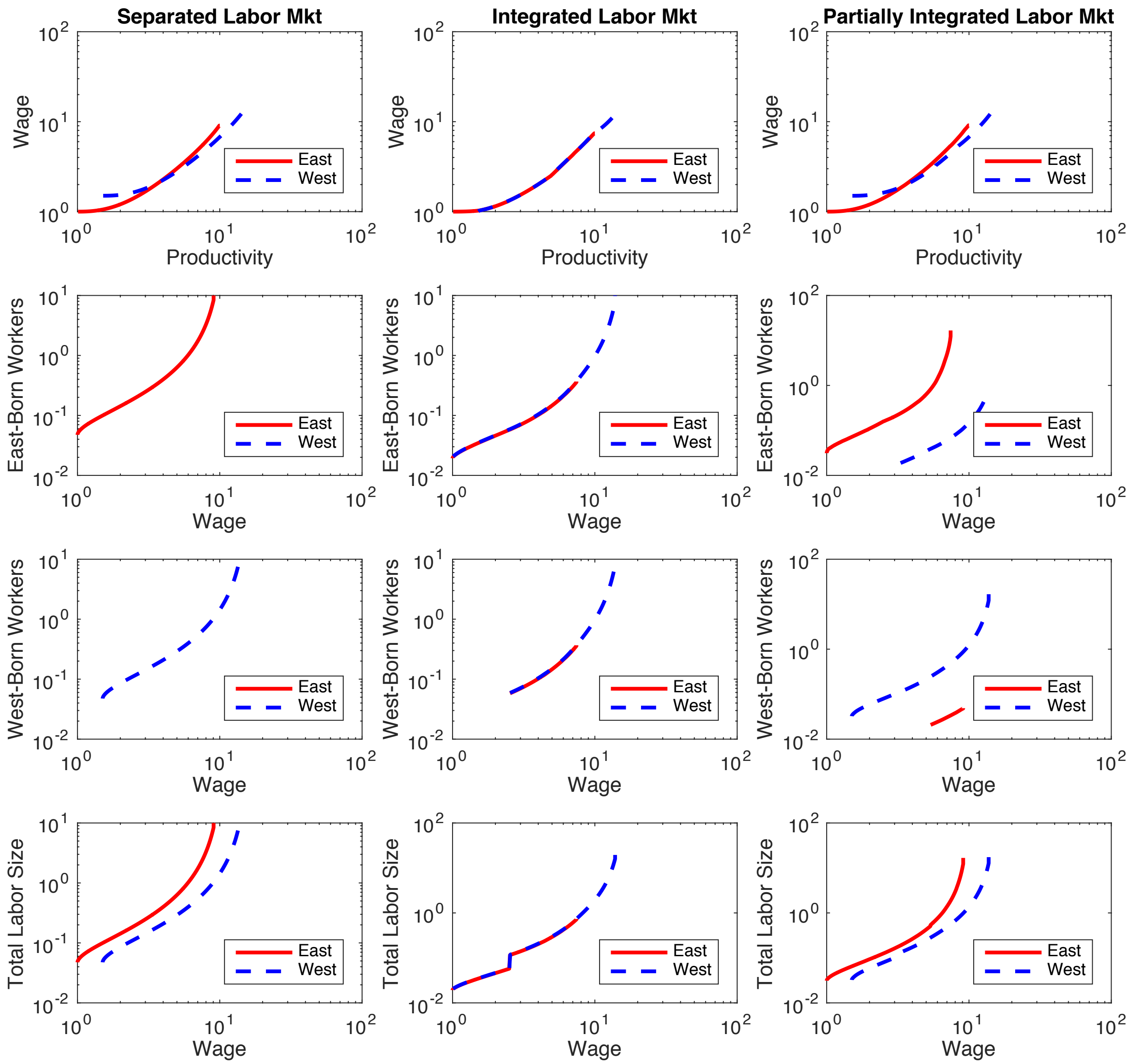
5.1 Inference Through the Lens of the Model

The first purpose of the model is to map the empirical results of Section 3 into three interpretable primitive parameters: the comparative advantage θ^i_j, the preference τ^i_j, and the labor offer friction φ^i_j. The structure of the model allows us to separately identify the sources of home bias and to estimate them, at the cost of relying on the model's assumptions.

Estimation Strategy. Our strategy to bring the model to the data is based on three main directives. First of all, we broadly aim to run, within the model, the same specification that we estimated in the data in section 3. In fact, we build the model with this purpose in mind. For example, the model naturally delivers the AKM-style regression of equation (9). However, the model is stripped down of several relevant features that are present in the data. Most importantly, in the model there is not a notion of distance or moving cost between locations since home bias is the only source of spatial friction. For this reason, our second directive is to use as estimation targets the regression coefficients that control for all the empirically relevant features not present in the model, such as distance. Finally,

[32]The sharp jump is driven by the discountinuity in labor supply around wage $w = b^W$. While this feature of the model is artificial, the insight is more general. Relatively high productivity firms are willing to cut their rents and increase wages to make their jobs appealing to workers from other regions.

Figure 8: Model Computation for three Special Cases



Notes: each column contains the solution of the equilibrium for one of the three special cases. The first row includes the wage function, for East and West firms, as a function of their productivity. The second and third rows plot respectively the number of East-born and West-born workers employed at firms either in the East or West as a function of the firms' wages. The fourth row includes the total labor size – i.e. the sum of East- and West-born workers – as a function of firms' wage.

we recognize that we are bringing a steady state model to an economy that might be not in steady state. Figure 2 shows that, in the last few years, wage convergence between regions is at most minor. However, Figures 17a and 17b show that, altough it represents only a small fraction of total gross flows, there is still net migration of East-born workers towards West Germany. Therefore, we try to target moments that are at most indirectly affected by the steady state assumption. For example, rather than targeting average wage by birth-place, which depend on the equilbrium allocation of workers to regions, we target average regional firm-wage. Similarly, rather than targeting unemployment rate, which is a steady state object, we target the rates at which workers moves into unemployment or between jobs. Our estimation strategy has implications for the interpretation of the results. We will spell them out when we present the results and the counterfactuals.

Units and Functional Form Assumptions. We let a unit interval of time to be one month.[33] We parametrize the vacancy cost function as $c_j(v) = c_{0,j} v^{c_{1,j}}$, and let the log of firms' productivity distributions be drawn from a Gamma distribution modulated by three parameters: the scale and shape parameters of the Gamma, that we assume common across both regions, and a relative productivity parameter $Z > 0$, that shifts the CDF of West – i.e. for all $\log p$, $\Gamma_W(\log p + Z) = \Gamma_E(\log p)$.[34] Considered these functional form assumptions, we have to pin down a total of 28 parameters. As usual, we first calibrate from our data the parameters that have a direct empirical counterpart without the need to solve the model. We then estimate the remaining parameters within the model through simulated method of moments.

Calibrated Parameters. We normalize the total mass of workers $D^E + D^W = 1$, and set the mass of each type of workers based on the share of workers born in a given region in the LIAB. We find $D^E = 0.32$ and $D^W = 0.68$. We set the mass of firms $M^E = 0.18$ and $M^W = 0.82$, using the number of establishments located in East and West Germany, respectively, in 2010 from the BHP. We estimate in the data birth-place-speficic separation rates using the monthly probability of East and West German workers of transitioning into unemployment during 2009-2014. These separation rates are $\delta^E = .0105$ and $\delta^W = .0072$, respectively. We set the value of being unemployed – b^i – to $0.8\underline{p}_j$ in both regions, where $\underline{p}_j$ is the lowest productiivty firm.[35]

Identification of Regional Parameters. We first discuss the identification of the basic parameters that would be present also in single region versions of our model: the relative West productivity Z,

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

[34]This assumption is motivated by figure 10, that shows that the size and wage distributions are very similar in East and West Germany, apart from the fact that the wage distribution in the East is shifted to the left.

[35]We choose an intermediate value of the value of unemployment that fall within the range usually shown in the literature. There is a very rich literature stufying the importance of the value of unemployment, in particular for cyclical labor fluctuations (See Shimer 2005; Hagedorn Manovskii 2008; Hornstein, Krusell, Violante; Karabarbunis Chodorov-Reich 2017). In our setting, however, the value of b^i is not determinant for the main parameters of interest, those that modulate the home bias.

the shape and scale parameters of the Gamma distribution – ξ_0 and ξ_1 –, the level and the curvature of the cost of posting vacancies $c_{0,j}$ and $c_{1,j}$, and the churning probability χ_j. While all parameters are jointly estimated, we provide an heuristic argument and describe the moment that mostly informs each parameter.

We run with model-generated data the AKM-regression of equation (2), and project the firm effects on a dummy for East firms. The relative West productivity mainly targets this moment. The vacancy parameters $c_{0,E}$ and $c_{0,W}$ pin down the number of posted vacancies and, as a result, the average arrival rate of offers in the economy. We thus target the rate at which workers move across jobs within each region. We use the joint distribution of firms' wages and sizes to pin down $c_{1,E}$, $c_{1,W}$, ξ_0 and ξ_1. As it is well known, in Burdett-Mortensen models the wage variance across firms is determined only by the firms' efforts to grow in size. In fact, the model generates a bijiection between firm wage and firm size. To be consistent with the model, we calculate – using the BHP data – the firm size distribution and the average wage by size, controlling for 3 digit industry fixed effects and labor characteristics. The results are in Figure 10. We then use ξ_0 and ξ_1 to target the skewness and the variance of the firm size distribution[36] and $c_{1,E}$ and $c_{1,W}$ to target the slopes of the size-wage relationships. The parameters $c_{1,E}$ and $c_{1,W}$ increase the curvature of the cost of posting vacancies, thus effectively modulating the strength of decreasing returns, thus helping to pin down the slope between wage and size.

Finally, we run, with model-generated data, the wage gain regression of equation (8) and use the estimated wage gains of within-regions job to job moves to pin down the value of χ^i. A larger value of the churning parameter reduces the average size of wage gains upon a job-job move, since churning moves are associated with – on average – a wage loss.

Identification of Home Bias Parameters. We next turn to the main parameters of interest, those that modulates the home bias.

Since the model generates the same augmented AKM-specification that we run in the data, we can recover directly the skill parameters θ_j^i from the data, subject to two normalization.[37] First, we normalize – without any loss of generality – $\theta_E^E = 1$. Second, we need to take a stand on how to distribute the home bias in skill (or comparative advantage) between East- and West-born. As we discuss in details in Section C, once we control for firms and workers fixed effects, we can include in specification (9) only one dummy for either East-born while working in the West, or viceversa. Intuitively, we need to assume that one type of workers (in this example, the West-born) is equally productive in both regions since, otherwise, we would not be able to pin down the firm-effects. As a result, the estimated dummy captures the sum of the home bias for both groups. We must then arbitrarly assign a share of the home bias to each group. Lacking guidance, we simply split it in half. Practically, given the small estimated home bias in skills, it does not matter for the results.

We normalize the birth-place to be the reference value – therefore $\tau_E^E = \tau_W^W = 1$. The home bias

[36] Due to the properties of the Gamma distribution, the shape and scale parameters modulates the skewness and variance of the productivity distribution, which then map into the size distribution through our model.

[37] Notice that θ_j^i can be directly calibrated outside of the model, even if they are discussed here.

parameters τ_W^E and τ_E^W are identified from the acceptance sets of job offers, which are themselves inferred from the wage gains of movers across regions, from regression (8). Consider workers making a job to job move from East to West. Their average wage gain is determined by three factors: i) the set of offers received; ii) the set of offers accepted among the received ones; iii) their wage distribution in the East. By assumption, i) is the same for East- and West-born; while iii) is an equilibrium object that the model determines and that is only indirectly affected by τ_W^E. Since the lower is τ_W^E, the fewer offers East-born workers would be willing to accept, then the model generates a monotonic relationship between relative wage gains and τ_W^E: the lower is τ_W^E, the larger should be the average wage gain of East workers relative to the one of West workers. A similar argument applies for τ_W^E. It is worthwhile to point out that our design does not allow for one of the two regions to provide a higher level of overall amenities since $\tau_E^E = \tau_W^W = 1$. We need to make this assumption to separately identify a home bias for East- and West-born, or otherwise we would encounter the same problem illustrated for θ: we would need to choose one unbiased reference group to pin down amenity differences.

Last, there are the four values of the frictional parameter φ_j^i. As already mentioned in Section 4, we normalize the wedges on the arrival rate of offers in such a way that they sum to one by region: for all j, $\sum_{i\in\{E,W\}} \varphi_j^i \bar{D}^i = 1$. Therefore we only have two free parameters to determine. We define the home bias in labor frictions to be the ratio $\eta_0 \equiv \left(\frac{\varphi_E^W}{\varphi_W^W}\right) / \left(\frac{\varphi_E^E}{\varphi_W^E}\right)$, which captures whether workers are more likely to receive offers from their home region. We run in the model the flows specification of equation (6), where distance between regions is simply equal to zero, and use η_0 to target the home bias in the destination fixed effects. As the fourth linear restriction, we let the average ratio be given by $\eta_1 = \frac{1}{2}\frac{\varphi_E^E}{\varphi_E^W} + \frac{1}{2}\frac{\varphi_W^E}{\varphi_W^W}$, where η_1 is bigger than one if East-born receive on average more offers than West-born. We find η_1 to target the ratio of the job to job mobility of East- and West-born workers.

The identification arguments described are necessarily heuristic, and rely on the indirect effects to be relatively minor. As an ex-post verification of our strategy, in Figure 9, we plot the joint distribution, obtained from Markov-chain simulations of the model, for the primitive parameters and the targeted moments. The relationships are monotonic, and the fit is strong – altough, as expected, it is not perfect since all the estimated parameters are random chains in these simulations.

Figure 9: Identification of Home Bias Parameters

Discussion of Model's Assumptions. The identification of home bias parameters rests on three assumptions which, following the original Burdett and Mortensen (1998) formulation, are built into the structure of our model.

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^i_j. For example, while we estimate φ^E_W 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.

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^i_j. In fact, under different wage setting 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 home bias, and thus are not a central aspect of our paper.

Third and last, as shown by Lemma 1, workers accept an offer if and only if it provides a higher flow utility. In fact, the continuation value is a monotonic function of flow utility, irrespective of current region. As a result, if, in fact, individuals move away from their home region in expectation of better future offers, we would underestimate the home bias. Alternatively, if, when individuals move away from home, they are trading off a higher flow wage in exchange for a future higher unemployment risk or slower wage growth, we would overestimate the home bias. In practice, the data does not support either one of these scenarios. Figure (4a) shows that future wage growth is very similar for workers moving away from home or towards home. Figure (5a) shows that unemployment risk is not differentially affected by a move towards or away from home.

5.2 Estimation and Model Fit [Extremely Preliminary - Tables Still Missing, but Preliminary Results are Discussed]

We estimate within the model the 9 regional parameters and the 4 home bias paramaters by targeting the 13 data moments discussed via an MCMC procedure based on Chernozhukov and Hong (2003), where we seek to minimize the squared percentage deviation between the model-implied moments and the moments in the data. Altough the model is just identified, it is — currently – not able to exactly match all the 13 moments. Table **??** presents the targeted moments in the data and compares them to the model-implied moments under our preferred calibration. Table **??** presents the estimated parameter values. The first row shows that the home region preference is roughly similar for both types of workers, and is in the order of $10 - 15\%$. The second row shows the estimated matching frictions. With these values, East-born workers receive approximately only one fifth as many offers from West German firms (and the same for West-born) as it would if $\varphi_j^i = 1$ for all (i, j). In the third row, we document that the observed average wage gap translate into an East German average productivity that is about 20% below that of the West.

5.3 The Aggregate Effects of Home Bias

We next use the estimated model to perform few quantitative exercises. All the results are included in Table (**??**).

The first exercise, in column (1) is to use the benchmark model to predict the long-run effects of home bias on wages by birth-region and allocation of labor across regions. Rows (1), (2) and (3) show the gap between East- and West-born in log wage, log firm wage, and log utility. As discussed, the model is in steady state, and does not have a role for distance. Therefore, these results should be interpreted as predicting the very long-run wage difference between East and West-born, after their allocation across regions is driven purely by home bias. They show that home bias alone can replicate more than half of the observed wage differences by home region. Row (3) shows that the utility gap is larger than the wage gap. The reason is simple: due to the higher wages, many East workers move to the West, however, while these workers enjoy high wage increases, their utility gains are much smaller, due to the large cost of living away from home. Rows (4), (5), and (6) show the overall share of workers in each region, and the shares of East-born and West-born. The model overpredicts, relative to the data, the share of labor in the West, and the share of workers that are employed in the foreign region. This result is not surprising, and predicts that the (slow) net migration observed in the data is bound to continue.

The second exercise studies the quantitative effects of home bias. In column (2), we solve the equilibrium assuming that workers like equally each region – $\tau_E^W = \tau_W^E = 1$; in column (3) we assume that workers are equally likely to receive wage offers from each region – i.e. $\varphi_j^i = 1$ for all (i, j). In column (4), we shut down both sources of home bias at the same time. We recompute the same statistics as for the first exercise, and add: log firm wage between the two regions (7); relative wage gains of moves to West and East, as targeted in the estimation (8,9); estimated home bias (10). Taken together, the results highlight few lessons.

First of all, reducing the home bias would lead the wage gap between East and West to reduce. The reason is that the home bias provides East German firms with a competitive advantage in hiring East workers, thus allowing them to retain workers without the need to post high wages. At the same time, even in the absence of any home bias, a sizable regional wage gap remains. The reason being that reallocation frictions alone are enough to allows low productive firms to survive paying lower wages. Second, shutting down the home bias would lead – as expected – to net reallocation of labor from East to West Germany. Third, the two sources of home bias have different impacts on the relationship between observed wage gap by birth-place and unobserved utility gap. When we shut down the regional preference, in column (2), the wage gap by birth reduces only marginally (in some calibration it even increases), while the utility gap shrinks sizably. The opposite happens when we shut down the regional offer bias, in column (3). The reason is as follows. In the benchmark estimated model, East-born workers are only willing to work in West-firms that pay a sufficiently high wage, and the fact that they reject all the lower paying firms pushes down the wage gap with West-born. If we remove the preference for the home-region, more East-born will accept to work even at low paying firms in the West. At the same time, workin in the West does not come anymore at a utility cost, thus reducing the utility gap. If, instead, we keep the estimated τ_j^i, but shut down the offers home bias, we will observe more and more East-workers moving to good firms in the West – since they receive offers from there. This reallocation of labor would push down the wage gap, but comes at a high utility cost. Overall, we conclude that home bias has important quantitative implications, and that distinguishing the sources of home bias is relevant to properly map the observed wage differences into welfare consequences.

5.4 Model External Validation [Incomplete]

We here explore, both qualitatively and quantitatively two external validation exercises.

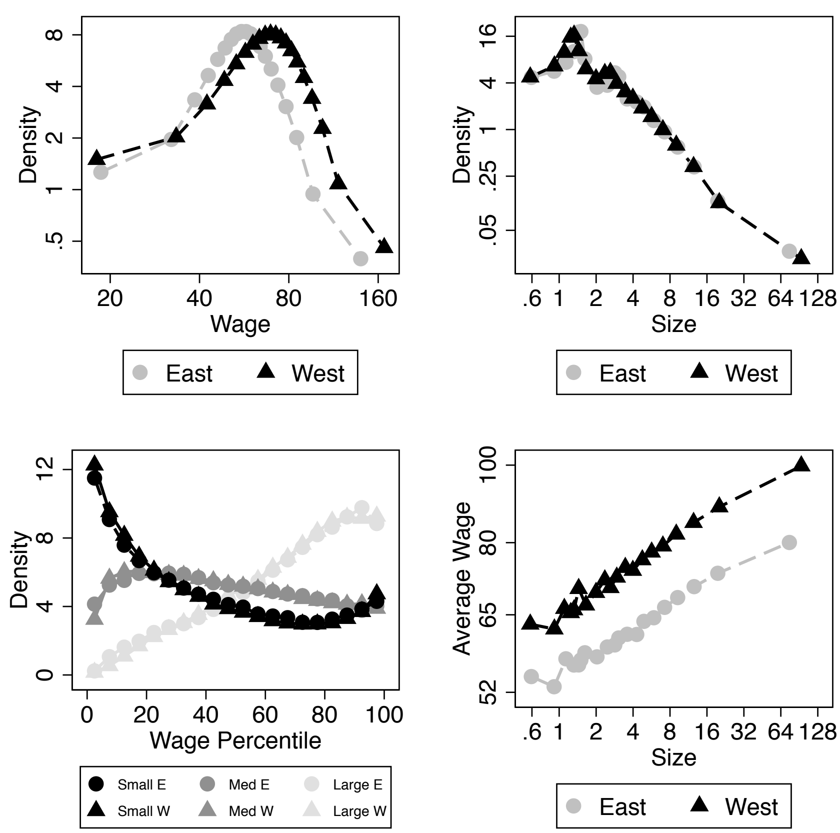
First we study empirically the relationship between firm size and firm wage. We show that, both in the model and in the data (see Figure 10) firm in West Germany pay a higher wage, conditional on their size. This result is generated by the home bias. In the absence of home bias, reallocation frictions would still allow East firms to survive, however, in the absence of home bias East firms should shrink, and – conditional on size – firms in the East and the West should offer the same wage. Home bias effectively partially shields East firms from the competition of the West, allowing them to retain workers.

Second, we use the model to compute the relative wage gains at migration for a mass zero, thus not affecting the equlibrium, of East- and West- workers that have $\tau_W^E = \tau_E^W = 1$. The model predicts this relative wage gains to be much smaller, since East- and West-born have the same acceptance sets. This exercise is meant to capture a cross-border move through commuting, that arguably has a smaller associated disulity from working in the other region, since you are still living in your home region.

6 Conclusion

[TBD]

Figure 10: Firm Wage and Size Distributions in East and West



References

Abowd, J., F. Kramarz, and D. Margolis (1999): "High Wage Workers and High Wage Firms," *Econometrica*, 67(2), 251–333.

Allen, T., and C. Arkolakis (2014): "Trade and the Topography of the Spatial Economy," *Quarterly Journal of Economics*, 129(3), 1085–1140.

BBSR (2009): "Regionaler Preisindex," in *Berichte*, vol. 30. BBSR, Bonn.

Bryan, G., and M. Morten (2017): "The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia," NBER Working Paper No. w23540.

Burchardi, K. B., and T. A. Hassan (2013): "The economic impact of social ties: Evidence from German reunification," *The Quarterly Journal of Economics*, 128(3), 1219–1271.

Burda, M. C. (2006): "Factor Reallocation in Eastern Germany after Reunification," *American Economic Review*, 96(2), 368–374.

Burda, M. C., and J. Hunt (2001): "From Reunification to Economic Integration: Productivity and the Labor Market in Eastern Germany," *Brookings Papers on Economic Activity*, 32(2), 1–71.

Burdett, K., and D. T. Mortensen (1998): "Wage Differentials, Employment Size, and Unemployment," *International Economic Review*, 39(2), 257–273.

Caliendo, L., L. D. Opromolla, F. Parro, and A. Sforza (2017): "Good and Factor Market Integration: A Quantitative Assessment of the EU Enlargement," NBER Working Paper No. 23695.

Card, D., J. Heining, and P. Kline (2013): "Workplace Heterogeneity and the Rise of West German Wage Inequality," *Quarterly Journal of Economics*, 128(3), 967–1015.

Chaney, T. (2008): "Distorted Gravity: The Intensive and Extensive Margins of International Trade," *American Economic Review*, 98(4), 1707–1721.

Chernozhukov, V., and H. Hong (2003): "An MCMC Approach to Classical Estimation," *Journal of Econometrics*, 115(2), 293–346.

Combes, P.-P., G. Duranton, and L. Gobillon (2008): "Spatial wage disparities: Sorting matters!," *Journal of Urban Economics*, 63(2), 723–742.

Eaton, J., and S. Kortum (2002): "Technology, Geography, and Trade," *Econometrica*, 70(5), 1741–1779.

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

Eckert, F., and M. Peters (2018): "Spatial Structural Change," mimeo, Yale University.

Fallick, B., and C. A. Fleischman (2004): "Employer-to-Employer Flows in the U.S. Labor Market: The Complete Picture of Gross Worker Flows," FEDS Working Paper No. 2004-34.

Fuchs-Schündeln, N., D. Krueger, and M. Sommer (2010): "Inequality Trends for Germany in the Last Two Decades: A Tale of Two Countries," *Review of Economic Dynamics*, 13(1), 103–132.

Glaeser, E. L., and D. C. Mare (2001): "Cities and skills," *Journal of labor economics*, 19(2), 316–342.

Gollin, D., D. Lagakos, and M. E. Waugh (2014): "The Agricultural Productivity Gap," *Quarterly Journal of Economics*, 129(2), 939–993.

Harris, J. R., and M. P. Todaro (1970): "Migration, unemployment and development: a two-sector analysis," *The American economic review*, 60(1), 126–142.

Hethey-Maier, T., and J. F. Schmieder (2013): "Does the Use of Worker Flows Improve the Analysis of Establishment Turnover? Evidence from German Administrative Data," NBER Working Paper No. 19730.

Hicks, J. H., M. Kleemans, N. Y. Li, and E. Miguel (2017): "Reevaluating Agricultural Productivity Gaps with Longitudinal Microdata," Discussion paper, National Bureau of Economic Research.

Hsieh, C.-T., and P. J. Klenow (2009): "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 124(4), 1403–1448.

Hunt, J. (2001): "Post-Unification Wage Growth in East Germany," *Review of Economics and Statistics*, 83(1), 190–195.

——— (2002): "The Transition in East Germany: When is a Ten-Point Fall in the Gender Wage Gap Bad News?," *Journal of Labor Economics*, 20(1), 148–169.

——— (2006): "Staunching Emigration from East Germany: Age and the Determinants of Migration," *Journal of the European Economic Association*, 4(5), 1014–1037.

Kennan, J., and J. R. Walker (2011): "The effect of expected income on individual migration decisions," *Econometrica*, 79(1), 211–251.

Krueger, A. B., and J.-S. Pischke (1995): "A Comparative Analysis of East and West German Labor Markets: Before and After Unification," in *Differences and Changes in Wage Structures*, ed. by R. B. Freeman, and L. F. Katz, pp. 405–446. University of Chicago Press.

Leiby, R. A. (1999): *The Unification of Germany, 1989-1990*. Greenwood Press, Westport, CT.

Moretti, E. (2011): "Local Labor Markets," in *Handbook of Labor Economics*, ed. by O. Ashenfelter, and D. Card, vol. 4B, chap. 14, pp. 1237–1313. Elsevier: North Holland.

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

Moser, C., and N. Engbom (2017): "Earnings Inequality and the Minimum Wage: Evidence from Brazil," mimeo, Columbia University.

Redding, S. J., and E. Rossi-Hansberg (2017): "Quantitative Spatial Economics," *Annual Review of Economics*, 9, 21–58.

Restuccia, D., and R. Rogerson (2008): "Policy Distortions and Aggregate Productivity with Heterogeneous Establishments," *Review of Economic Dynamics*, 11(4), 707–720.

Roback, J. (1982): "Wages, Rents, and the Quality of Life," *Journal of Political Economy*, 90(6), 1257–1278.

Rosen, S. (1979): "Wage-Based Indexes of Urban Quality of Life," in *Current Issues in Urban Economics*, ed. by P. Mieszkowski, and M. Straszheim. Johns Hopkins University Press.

Sjaastad, L. A. (1962): "The costs and returns of human migration," *Journal of political Economy*, 70(5, Part 2), 80–93.

Smolny, W. (2009): "Wage Adjustment, Competitiveness and Unemployment - East Germany after Unification," *Jahrbücher für Nationalökonomie und Statistik*, 229(2+3), 130–145.

Young, A. (2013): "Inequality, the Urban-Rural Gap, and Migration," *Quarterly Journal of Economics*, 128(4), 1727–1785.

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 excacerbated by the break-up and transfer of unproductive East German conglomerates to private owners, who usually downsized or closed plants.[38]

[38]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 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 11). 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 $\frac{2}{3}$. Aggregate GDP in East and West, respectively, in a 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 separetely for East and West Germany, employment L, capital K and GDP Y.[39] We can then use the previous formula to compute the implied total factor productivity term, A. We rewrite the previous equation in per capita terms, that is

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

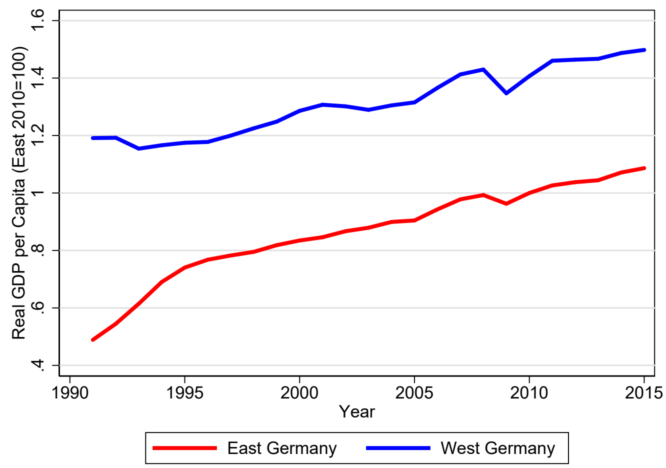
where $y \equiv \frac{Y}{N}$, $k \equiv \frac{K}{N}$, $n \equiv \frac{L}{N}$ and N is total population, also observed in the data. Last, we decompose the percentage difference in GDP per capita between West and East into its three components, that is

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

In Figure 12 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 larger establishment component of West German establishments we find in our AKM decomposition in the main text.

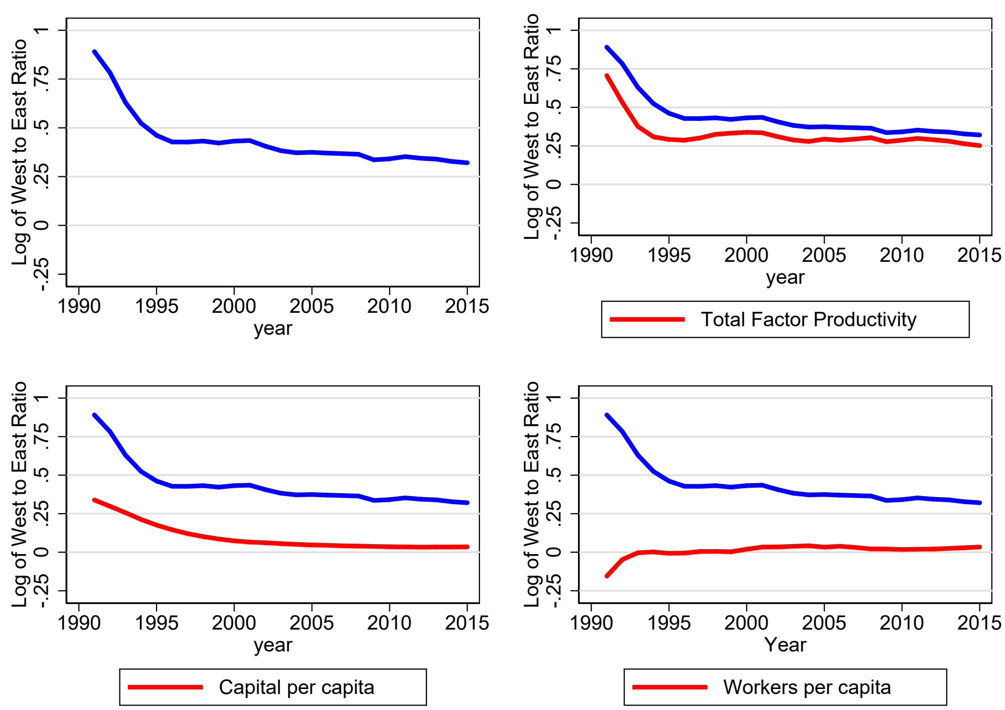
[39] We compute all statistics excluding Berlin to be consistent with the main text.

Figure 11: Real GDP per Capita



Sources: Volkswirtschaftliche Gesamtrechnungen der Laïder (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 2009 from the BBSR.

Figure 12: 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. Real GDP in 2010 prices is obtained from VGRdL and divided by total population, then adjusted by the cost of living difference in 2009 from the BBSR. 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.

C 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. Equation (2) states

$$w_{it} = \alpha_i + \psi_{J(i,t)} + BX_{it} + \epsilon_{it}, \tag{26}$$

where i indexes full-time workers, t indexes time, and $J(i,t)$ indexes worker i's establishment at time t.[40] 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, 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.[41]

Identification of the Model with Comparative Advantage

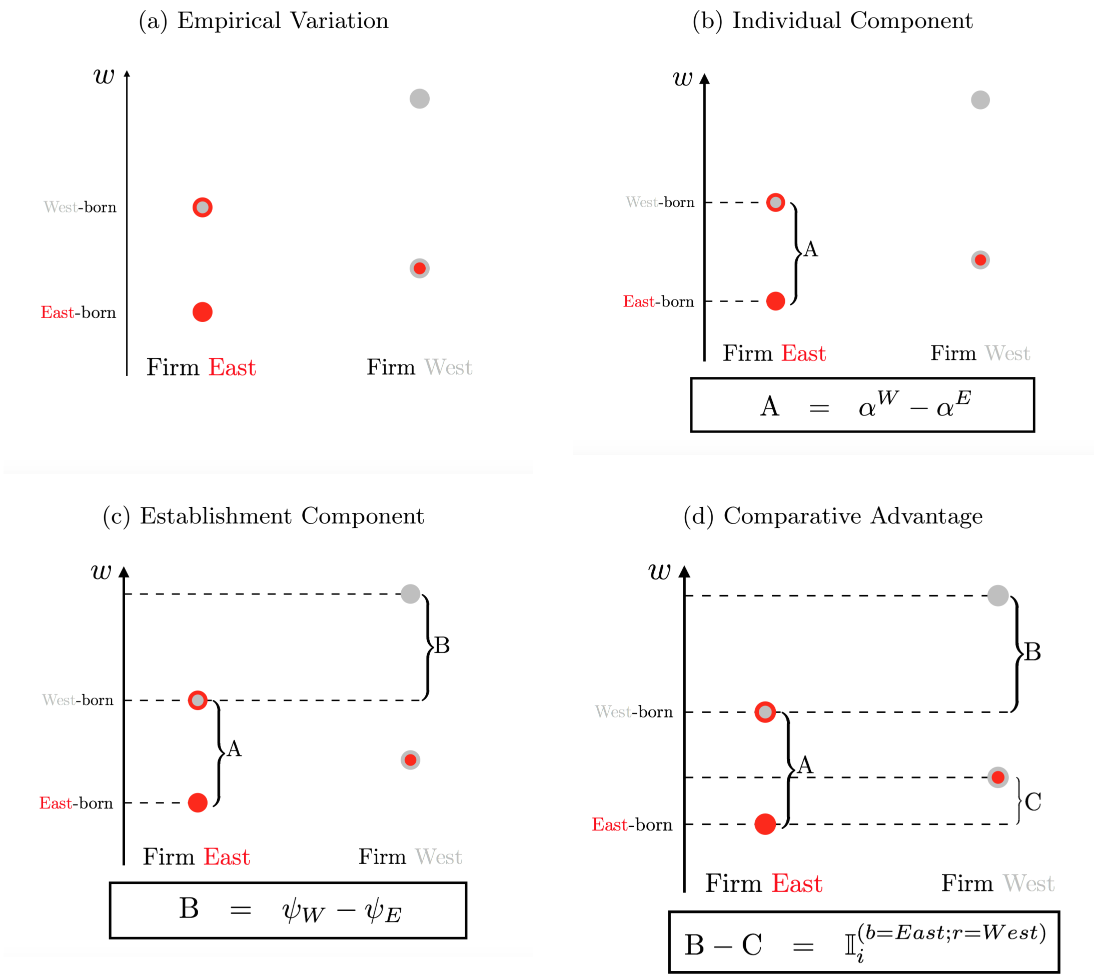
Consider the wages earned by four workers: an East-born and a West-born working at a given establishment in the East, and an East-born and a West-born working at a given establishment in the West. Figure 13a plots an example of these workers' wages, where the x-axis is the identity of the establishment, 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 13b-13d then show how these data identify the three AKM components. First, as depicted in Figure 13b, the individual components are identified from comparing the wages of two workers that are 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 13c highlights that the establishment components are identified by comparing a worker at two different establishments. If the same 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 13d illustrates how the comparative advantage is identified. If two workers employed at the same establishment in the East have a different wage differential at an establishment in the West than at an establishment in the East, then this gap in the wage differentials identifies the comparative advantage.

[40] 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.

[41] 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.

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 an East German worker's wage is relatively lower than a 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. We will attribute the comparative advantage coefficient to the East German worker employed in the West.

Figure 13: Identification of the AKM Components



Note: The figure illustrates the wage of four 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.

D Proofs

D.1 Proof of Proposition 1 2

The proof of the general case is constructive, and solves the optimization problem to show that it leads to a system of differential equations, for which we provide analytical expressions.

Consider first the wage posting problem (17). Using equation (23), the first-order condition of this problem is

$$\frac{\left(pZ_j - w_j\left(p\right)\right)\left(\sum_{i\in\mathbb{I}}\theta_j^i \frac{\partial l_j^i(w_j(p))}{\partial w}\right)}{\left(\sum_{i\in\mathbb{I}}\theta_j^i l_j^i\left(w_j\left(p\right)\right)\right)} \quad = \quad 1, \tag{27}$$

where for any type i we have $l_j^i(w_j(p)) > 0$ if $\theta_j^i \tau_j^i w_j(p) \geq b^i$ and $l_j^i(w_j(p)) = 0$ otherwise. Define the ordered set for each region j

$$\mathbb{N}\left(j\right) \equiv \left\{\frac{b^{\iota(j,1)}}{\theta_j^{\iota(j,1)}\tau_j^{\iota(j,1)}}, ..., \frac{b^{\iota(j,I)}}{\theta_j^{\iota(j,I)}\tau_j^{\iota(j,1)}}\right\},$$

where the set $\mathbb{N}\left(j\right)$ ranks worker types according to the minimum wage rate they require to work in region j, starting with the worker type that requires the lowest wage. Specifically, $\iota\left(j,x\right)$ is an operator such that $\iota\left(j,1\right) = \arg\min_{i\in\mathbb{I}} \frac{b^i}{\theta_j^i\tau_j^i}$, $\iota\left(j,2\right) = \arg\min_{i\in\mathbb{I}\setminus\iota(j,1)} \frac{b^i}{\theta_j^i\tau_j^i}$, and so on, up to $\iota\left(j,I\right) = \arg\max_{i\in\mathbb{I}} \frac{b^i}{\theta_j^i\tau_j^i}$.

Next, differentiating equation (27) with respect to p and using equation (23), we obtain a set of differential equations for wages $\left\{\frac{\partial w_j^{\iota(j,1)}(p)}{\partial p}, ..., \frac{\partial w_j^{\iota(j,I)}(p)}{\partial p}\right\}$ of the form

$$\frac{\partial w_j^{\iota(j,n)}(p)}{\partial p} = -\frac{\left(pZ_j - w_j^{\iota(j,n)}(p)\right)\sum_{i=1}^n \theta_j^{\iota(j,i)}\left(\frac{2\varphi_j^{\iota(j,i)}\delta^{\iota(j,i)}\bar{D}^i\left(\frac{\partial q_j^{\iota(j,i)}(p)}{\partial p}\right)}{\left[q_j^{\iota(j,i)}(p)\right]^3}\right)}{\left(\sum_{i=1}^n \theta_j^{\iota(j,i)}\frac{\varphi_j^{\iota(j,i)}\delta^{\iota(j,i)}\bar{D}^{\iota(j,i)}}{\left[q_j^{\iota(j,i)}(p)\right]^2}\right)} \tag{28}$$

which define firms' optimal wage posting within each non-overlapping interval $w_j^{\iota(j,n)}(p) \in [\frac{b^{\iota(j,n)}}{\theta_j^{\iota(j,n)}\tau_j^{\iota(j,n)}}, \frac{b^{\iota(j,n+1)}}{\theta_j^{\iota(j,n+1)}\tau_j^{\iota(j,n+1)}})$ for $n < I$, and $w_j^{\iota(j,I)} \in [\frac{b^{\iota(j,I)}}{\theta_j^{\iota(j,I)}\tau_j^{\iota(j,I)}}, \infty)$. The overall differential equation for wage, $\frac{\partial w_j(p)}{\partial p} = H_j\left(\left\{q_j^i\left(p\right)\right\}_{j\in J, i\in I}, \{w_j (\right.$ is going to be given by the union of the piece-wise ones shown in (28). To find this function, we need to know the relevant domains of each region's productivity distribution that map into each wage support.

Towards this aim, we now show how to determine the cutoffs $\hat{p}_j^i$ as defined in Proposition 1, which provide the lowest productivity firm in region j hiring workers of type i, and consequently the boundary conditions for the differential equation. Define $\pi_j^{\iota(j,n)}(p_j)$ to be the profit function for a firm p_j that posts a wage high enough to attract workers of type $\iota(j,n)$ and behaves optimally, hence

$$\pi_j^{\iota(j,n)}(p_j) = \max_{w \geq \frac{b^{\iota(j,n)}}{\theta_j^{\iota(j,n)} \tau_j^{\iota(j,n)}}} (p_j Z_j - w) \sum_{i=1}^{n} \theta_j^{\iota(j,i)} l_j^{\iota(j,i)}(w).$$

Next, define $\underline{\tilde{p}}_j = \min p_j$ s.t. $p_j \geq \frac{b^{\iota(j,1)}}{\theta_j^{\iota(j,1)} \tau_j^{\iota(j,1)}}$. The firm with productivity $\underline{\tilde{p}}_j$ is the lowest productivity firm active in region j, since firms with $p_j < \underline{\tilde{p}}_j$ would make losses at the wage necessary to attract even the lowest reservation wage workers. Similarly, define for each $n \geq 2$

$$\tilde{p}_j^{\iota(j,n)} = \min p_j \quad s.t. \quad \pi_j^{\iota(j,n)}(p_j) \geq \max_{x<n} \pi_j^{\iota(j,x)}(p_j), \tag{29}$$

where $\tilde{p}_j^n$ is thus the lowest productivity firm that has a weakly higher profit by hiring workers of types $\iota(j,1), ..., \iota(j,n)$ rather than any subset of workers of type lower, in the reservation wage sense, than n. In general, it may be the case that $\tilde{p}_j^{\iota(j,n+1)} < \tilde{p}_j^{\iota(j,n)}$, for example if posting a higher wage and attracting type $n+1$ as well allows a firm to significantly raise its profits relative to the case in which only workers up to type n are hired. Therefore, we define

$$\hat{p}_j^{\iota(j,n)} = \min_{x \geq n} \tilde{p}_j^{\iota(j,x)}. \tag{30}$$

Equation (30) defines the productivity of the marginal firm that hires workers of type i, $\hat{p}_j^i$ for $i \in \mathbb{I}$.

Since it is possible to have $\hat{p}_j^i = \hat{p}_j^{i'}$ for some or even all pairs (i, i') of worker types, we define $\mathbb{D}$ as the set of worker types that have distinct cutoffs. By continuity of the profit function, the $n \in \mathbb{D}$ types are the ones that satisfy

$$\hat{p}_j^{\iota(j,n)} = \tilde{p}_j^{\iota(j,n)}.$$

Due to the usual complementarity argument between productivity and size, it must be that $\hat{p}_j^{\iota(j,n+1)} \geq \hat{p}_j^{\iota(j,n)}$ for all n, that is, higher reservation wage types are hired on average by higher productivity firms within the same region j. Call d_x the x^{th} element of $\mathbb{D}$.[42] We need to find $|\mathbb{D}|$ restrictions to solve for cutoffs values $\hat{p}_j^{\iota(j,d_x)}$ for $d_x \in \mathbb{D}$. Given these $|\mathbb{D}|$ cutoffs, we can find the cutoffs for the remaining types $n \notin \mathbb{D}$ using equation (30).

For the first cutoff, we have

$$\hat{p}_j^{\iota(j,1)} = \underline{\tilde{p}}_j.$$

Then, since the profit function $\pi_j^{\iota(j,n)}(p_j)$ is continous,[43] it must be that for all $d_x \in \mathbb{D}$ with $x \geq 2$, we

[42] For example, assume that $I = 4$ and that $\hat{p}_j^{\iota(j,1)} < \hat{p}_j^{\iota(j,2)} = \hat{p}_j^{\iota(j,3)} < \hat{p}_j^{\iota(j,4)}$, therefore the set $\mathbb{D} = \{1, 3, 4\}$, adn $d_1 = 1$, $d_2 = 3$, and $d_3 = 4$.

[43] This profit function is continous due to the fact that we are defining it keeping constant the set of hired types.

have

$$\pi_j^{\iota(j,d_{x-1})}\left(\hat{p}_j^{\iota(j,d_{x-1})}\right)=\pi_j^{\iota(j,d_x)}\left(\hat{p}_j^{\iota(j,d_x)}\right),$$

which gives us the remaining $|\mathbb{D}|-1$ restrictions. Thus, we have found the restrictions for the I cutoffs.

The boundaries of the differential equation are then given by, for each $n\in\mathbb{D}$

$$w_j\left(\hat{p}_j^{\iota(j,n)}\right) = \arg \max_{w\geq\frac{b^{\iota(j,n)}}{\theta_j^{\iota(j,n)}\tau_j^{\iota(j,n)}}} \left(p_jZ_j-w\right)\sum_{i=1}^{n}\theta_j^{\iota(j,i)}l_j^{\iota(j,i)}(w).$$

Therefore, we have shown that wage function satisfies the following step-wise differential equation

$$\frac{\partial w_j(p)}{\partial p} = -\frac{\left(pZ_j-w_j^{\iota(j,n)}(p)\right)\sum_{i=1}^{n}\theta_j^{\iota(j,i)}\left(\frac{2\varphi_j^{\iota(j,i)}\delta^{\iota(j,i)}\bar{D}^{i}\left(\frac{\partial q_j^{\iota(j,i)}(p)}{\partial p}\right)}{\left[q_j^{\iota(j,i)}(p)\right]^3}\right)}{\left(\sum_{i=1}^{n}\theta_j^{\iota(j,i)}\frac{\varphi_j^{\iota(j,i)}\delta^{\iota(j,i)}\bar{D}^{\iota(j,i)}}{\left[q_j^{\iota(j,i)}(p)\right]^2}\right)}\text{for } p\in\left[\hat{p}_j^{\iota(j,n)},\hat{p}_j^{\iota(j,n+1)}\right),$$

where the cutoffs and the boundaries are as previously described, and we define $\hat{p}_j^{\iota(j,I+1)}=\infty$.

We next turn to the derivation of the derivative of the separation rate with respect to p, $\frac{\partial q_j^i(p)}{\partial p}$, which appears in the differential equation for the wage. From (22), this derivative depends on the distribution of wage offers F from each region x. Since the wage is increasing in firms' productivity, the probability that a worker of type i in region j receiving utility flow $u=\theta_j^i\tau_j^iw_j(p)$ rejects a random offer from region x is given by

$$F_x\left(\frac{\theta_j^i\tau_j^iw_j(p)}{\theta_x^i\tau_x^i}\right)=\frac{\int^{\psi_{jx}^i(w_j(p))}v_x(z)\gamma_x(z)\,dz}{\lambda_x}, \tag{31}$$

using equation (19). Equation (31) contains a productivity cut-off $\psi_{jx}^i(w)$, which is defined via

$$\begin{cases}\theta_x^i\tau_x^iw_x\left(\psi_{jx}^i(w_j(p))\right)=\theta_j^i\tau_j^iw_j(p) & \text{if } \psi_{jx}^i(w_j(p))\in\left[\underline{p}_x,\bar{p}_x\right]\\ \psi_{jx}^i(w_j(p))=\bar{p}_x & \text{if } \theta_x^i\tau_x^iw_x(\bar{p}_x)<\theta_j^i\tau_j^iw_j(p)\\ \psi_{jx}^i(w_j(p))=\underline{p}_x & \text{if } \theta_x^i\tau_x^iw_x\left(\underline{p}_x\right)>\theta_j^i\tau_j^iw_j(p).\end{cases} \tag{32}$$

Intuitively, $\psi_{jx}^i(w_j(p))$ is the firm with the highest productivity in region x whose offer makes a worker of type i in region j earning $w_j(p)$ just indifferent between accepting and rejecting, provided that such a firm exists. For wage offers made by firms in the same region j as the worker, $\psi_{jx}^i(w_j(p))=p$. If no firm exists in region x to provide the worker with a sufficiently high utility, the probability that the worker accepts is zero (second line). The acceptance probability is one if any offer would induce the worker to move (third line). For unemployed workers, the expressions are identical with $w_j(p)=\frac{b^i}{\theta_j^i\tau_j^i}$.

Next, rewrite equation (22) as a function of p, by substituting the utility $u = \theta_j^i \tau_j^i w_j(p)$

$$q^i\left(\theta_j^i \tau_j^i w_j(p)\right) = \delta^i + \sum_{x\in\mathbb{J}} \varphi_x^i \lambda_x \left(1 - F_x\left(\frac{\theta_j^i \tau_j^i w_j(p)}{\theta_x^i \tau_x^i}\right)\right),$$

differentiate with respect to p, use (31), and the definition of $q_j^i(p)$, to yield a differential equation for the separation rate $q_j^i(p)$

$$\frac{\partial q_j^i(p)}{\partial p} = -\sum_{x\in\mathbb{J}} \varphi_x^i \left(\frac{\partial \psi_{jx}^i(w_j(p))}{\partial p}\right) v_x\left(\psi_{jx}^i(w_j(p))\right) \gamma_x\left(\psi_{jx}^i(w_j(p))\right). \tag{33}$$

Equation (33) defines the $J \times I$ differential equations for the separation rates introduced in the proposition: $\frac{\partial q_j^i(p)}{\partial p} = K_j^i\left(\left\{q_j^i(p)\right\}_{j\in J, i\in I}, \{w_j(p)\}_{j\in J}\right)$. The equation shows that the change in the separation rate is negatively related to the change in the marginal firm, which in turn depends on the slope of the wage functions. When the wage schedule in region x is relatively flat compared to the wage schedule in region j, a small change in p can significantly reduce the separation rate of workers from j to x.

We then need to find the $J \times I$ boundary conditions for the separation rate. For each type of worker i, these are given by the rate at which the worker leaves the most productive firm in each region j,

$$q_j^i(\bar{p}_j) = \delta^i + \sum_{x\in\mathbb{J}} \varphi_x^i \int\limits_{\psi_{jx}^i(w_j(p))} v_x(z)\, \gamma_x(z)\, dz. \tag{34}$$

In the region in which the most productive firm provides the highest utility flow for this type of worker, indexed by $\bar{p}_j^i = \operatorname{argmax}\left\{\theta_{j'}^i \tau_{j'}^i w_{j'}(\bar{p}_{j'})\right\}_{j'=1}^{\mathbb{J}}$, the worker only quits exogenously and therefore $q_j^i(\bar{p}_j^i) = \delta^i$.

Summing up, we have shown that the solution of the equilibrium satisfies a set of differential equations, with a rich set of boundary conditions. Therefore we have proved Proposition 1.

E Example Cases of Spatial Frictions

If spatial frictions are present, then local labor markets are partially shielded from competition from other regions. Firms that face less competition are able to grow more without the need to offer high wages, and hence are larger on average for a given wage. We define a measure of relative labor market slack between different regions to capture this effect of spatial frictions in one summary statistic, which we then use to study the effect of these frictions.

Definition 4: Relative Labor Market Slack. *The relative labor market slack between regions j' and j for at wage level w is*

$$\kappa_{j'j}(w) \quad \equiv \quad \arg\min_{\kappa \in \mathbb{R}^+} \left| l_{j'}(w) - l_j(\kappa w) \right|.$$

The average relative labor market slack between regions j' and j is

$$\kappa_{j'j} = \int \kappa_{j'j}\left(w_{j'}(p)\right) \gamma_{j'}(p)\, dp.$$

Note that $\kappa_{j'j}$ is larger than one if the labor market in region j' is on average slacker than the one in region j, i.e., if firms in region j need to pay on average a higher wage to be as large as those in region j'. Furthermore, $\kappa_{j'j}$ solves $l_{j'}(w) - l_j\left(\kappa_{j'j}(w)\, w\right) = 0$ with equality for wages w where $l_{j'}(w)$ is within the range of firm sizes in region j'.

Distinct Labor Markets. Consider a distinct labor market where each worker type is willing to work in only one region.

Lemma 2. *Let $I = J$, and if $i = j$ then $\tau_j^i = \tau$, $\theta_j^i = \theta$, and $\varphi_j^i = \varphi$. Let the spatial bias satisfy $\Lambda^i(i,j) = \infty$ if $j \neq i$.*[44] *Assume that there is a Z_j such that $\Gamma_j(Z_j p) = \Gamma(p)$, $b^j = Z_j b$, and $c_j(v) = Z_j c(v)$. Finally, assume that $D^i = D$ and $\delta^i = \delta$. Then, the equilibrium is given by two functions $w(p)$ and $l(p)$ such that for all j and i*

$$w_j(p) = Z_j w(Z_j p)$$

and

$$l_j^i(Z_j p) = \begin{cases} l(p) & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}.$$

Moreover, the relative labor market slack between any two regions is identical for each w and given by

$$\kappa_{j'j}(w) = \kappa_{j'j} = \frac{Z_j}{Z_{j'}}$$

[44] Notice that the following implies that if $i \neq j$, either $\tau_j^i = 0$ or $\theta_j^i = 0$, or $\varphi_j^i = 0$.

and reallocation frictions satisfy

$$\begin{aligned}\phi_j\left(Z_j p\right) &= \phi\left(p\right)\\ \phi_j &= \phi.\end{aligned}$$

Proof. See Appendix E.1. □

Lemma 1 illustrates that, in this special case, each region are rescaled version of one another, shifted by the region specific parameter Z_j, which can be interpreted as an aggregate productivity parameter. The spatial bias between regions is infinite and therefore there is no mobility across regions. Moreover, for a given level of wage, firms in the low aggregate productivity regions face a slacker labor market, since they face effectively less competition from other firms. This first case matches some key salient feature shown in Section 3, in particular the wage gap between East and West and the shifted job ladders. However, it clearly misses the extensive reallocation of workers across regions.

Unified Labor Market without Spatial Frictions. Next, we consider a case where all regions are part of one unified labor market, with heterogenous worker types, but no spatial frictions.

Lemma 3. *Assume that for all j, $c_j\left(v\right) = c\left(v\right)$, and that there are no spatial frictions, that is*

$$\Upsilon = 0.$$

Then, conditional on productivity, wages and reallocation frictions are identical in all regions and the relative labor market slack is equal to one: for all j', j , p and w

$$\begin{aligned}w_{j'}(p) &= w_j(p)\\ \phi_{j'}\left(p\right) &= \phi_j\left(p\right).\\ \kappa_{j'j}\left(w\right) &= 1.\end{aligned}$$

Nonetheless, the average wage and aggregate reallocation frictions vary as a function of productivity distribution: the average wage is an increasing function of average firm productivity, while the reallocation friction is a decreasing one.

Proof. See Appendix E.2. □

E.1 Proof of Lemma 12

The proof proceeds in two steps. First, we follow the standard steps in Burdett and Mortensen (1998) to show that the equilibrium in a closed economy can be described by two differential equations. We then show that if we have an equilibrium in the West, then the conjectured equilibrium relationships constitute an equilibrium in the East.

Step 1: Equilibrium in the closed economy

Consider the problem described in the main text for an economy in isolation, i.e., $\varphi = 0$. We normalize the mass of workers in the economy to $N = 1$. The separation rate from equation (**??**) is

$$q(w) = \delta + \theta + \lambda \left[1 - F(w)\right]$$

and the hiring rate $h(w)$ from equation (**??**) is

$$h(w) = u + (1-u)G(w).$$

We have the flow equations

$$\dot{u} = (\delta + \theta)(1-u) - \lambda u$$

and

$$\dot{D}(w) = \lambda F(w)\, u - (\delta+\theta) D(w) - \lambda\left(1 - F(w)\right) D(w).$$

In steady state, these equations lead to

$$\frac{u}{1-u} = \frac{\delta+\theta}{\lambda}$$

and

$$G(w) = \frac{\delta F(w)}{\delta + \lambda\left(1 - F(w)\right)}. \tag{35}$$

As in the main text, equation (**??**), firms maximize profits by choosing vacancies and wages:

$$\max_{(w,v)\geq(b,0)} \left[(p-w)\frac{h(w)}{q(w)} v - c(v)\right].$$

Define profits per vacancy as $\pi(p,w) = (p-w)h(w)/q(w)$. The optimal vacancy posting satisfies

$$\pi^*(p) = c'(v) \quad \Rightarrow \quad v = \xi(\pi^*(p)),$$

where ξ is the inverse marginal cost function and $\pi^*(p)$ are the profits under the profit-maximizing wage policy.

To obtain the wage function, we use the expressions for $h(w)$ and $q(w)$ and the steady state equations for unemployment and $G(w)$ to obtain

$$\pi(p,w) = \frac{(\delta+\theta)(p-w)}{\left[\delta + \theta + \lambda[1 - F(w)]\right]^2}.$$

The first-order condition of this expression yields

$$\frac{2\lambda F'(w)(p-w)}{\delta + \theta + \lambda\left[1 - F(w)\right]} = 1. \tag{36}$$

Using the expression for $F(w)$ from equation (**??**) and differentiating with respect to p gives

$$F'(w(p))w'(p) = \frac{v(p)\gamma(p)}{\int_b^{\bar{p}} v(z)\gamma(z)dz} = \frac{v(p)\gamma(p)}{\bar{\lambda}},$$

where $w(p)$ is the wage posting as a function of productivity and the second equality follows from (**??**). Combining this expression with equation (36) yields a differential equation for the wage function

$$w'(p) = \frac{2v(p)\gamma(p)(p - w(p))}{q(p)}. \tag{37}$$

We can re-write this expression by noting that the overall separation rate as a function of productivity is

$$q(p) = \delta + \theta + \lambda\left[1 - F(w(p))\right] = \delta + \theta + \int_p^{\bar{p}} v(z)\gamma(z)dz,$$

which has the derivative

$$q'(p) = -v(p)\gamma(p).$$

Applying this expression to equation (37) gives

$$w'(p) = \frac{-2q'(p)(p - w(p))}{q(p)},$$

which has the boundary condition

$$w(\underline{p}) = b.$$

On the other hand, from optimal vacancy posting we can re-express the derivative of the separation function as

$$q'(p) = -\xi\left(\frac{(\delta+\theta)(p - w(p))}{\left[q(p)\right]^2}\right)\gamma(p), \tag{38}$$

which has boundary condition

$$q(\bar{p}) = \delta + \theta.$$

The two differential equations together with the boundary conditions provide the solution to the problem without cross-regional mobility.

Step 2: Equilibrium in the East

Assume that $\Gamma_E(\kappa p) = \Gamma_W(p)$ with $\kappa < 1$, and $b_E = \kappa b_W$, $\delta_E = \delta_W$, and $\bar{c}_E = \kappa\bar{c}_W$ as given in the proposition. We show that if under these assumptions

$$\left(\lambda_W, w_W\left(p\right), q_W\left(p\right), G_W\left(w(p)\right), F_W\left(w(p)\right)\right)$$

are an equilibrium in the West, then

$$\left(\lambda_E, w_E\left(p\right), q_E\left(p\right), G_E\left(w(p)\right), F_E\left(w(p)\right)\right)$$

with

$$\begin{aligned}
\lambda_E &= \lambda_W \\
w_E(\kappa p) &= \kappa w_W(p) \\
q_E(\kappa p) &= q_W(p) \\
G_E(w(\kappa p)) &= G_W(w(p)) \\
F_E(w(\kappa p)) &= F_W(w(p))
\end{aligned}$$

are an equilibrium in the East.

We begin by verifying that our conjectures $q_E(\kappa p) = q_W(p)$ and $w_E(\kappa p) = \kappa w_W(p)$ are correct. Rewriting equation (38) and using the expression for optimal vacancies (**??**), we have for West Germany that

$$q_W(p) = \left(-\frac{\delta(p - w_W(p))}{\bar{c}_W [q_W'(p)]^\chi}\right)^{\frac{1}{2}} \gamma_W(p)^{\chi/2}.$$

If our guess that $q_E(\kappa p) = q_W(p)$ is correct, then $q_E'(\kappa p) = \frac{1}{\kappa} q_W'(p)$. From the assumptions for Γ_E and Γ_w we have that $\gamma_E(\kappa p) = \frac{1}{\kappa}\gamma_W(p)$. Replacing these expressions in the equation for East Germany yields

$$q_E(\kappa p) = \left(-\frac{\delta(\kappa p - w_E(\kappa p))}{\bar{c}_E \left[\frac{1}{\kappa} q_W'(p)\right]^\chi}\right)^{\frac{1}{2}} \left(\frac{1}{\kappa}\right)^{\chi/2} \gamma_W(p)^{\chi/2}$$

Given our conjecture for the wage function,

$$q_E(\kappa p) = \left(-\frac{\kappa\delta(p - w_W(p))}{\bar{c}_E [q_W'(p)]^\chi}\right)^{\frac{1}{2}} \gamma_W(p)^{\chi/2}.$$

Using the fact that $\bar{c}_E = \kappa \bar{c}_W$ yields the desired result, and so indeed $q_E(\kappa p) = q_W(p)$.

We also need to verify the guess for the wage. Our conjecture implies that $w_E'(\kappa p) = w_W'(p)$. Using the differential equation for the wage and the relationship between the separation function in the East and in the West, we obtain

$$w_E'(\kappa p) = \frac{-2q_E'(\kappa p)(\kappa p - w_E(\kappa p))}{q_E(\kappa p)} = \frac{-2\frac{1}{\kappa} q_W'(p)(\kappa p - \kappa w_W(p))}{q_W(p)} = w_W'(p).$$

Thus this guess is also verified.

Note that the boundary conditions hold. For the wage function,

$$\kappa w_W(\underline{p}) = \kappa b_W \quad \Leftrightarrow \quad w_E(\kappa \underline{p}) = b_E.$$

For the separation function,

$$q_W(\bar{p}) = q_E(\kappa \bar{p}) = \delta + \theta.$$

We next verify that $\lambda_W = \lambda_E$. From optimal vacancy posting,

$$v_E(\kappa p) = \left[\frac{\delta(\kappa p - w_E(\kappa p))}{\bar{c}_E [q_E(\kappa p)]^2}\right]^{1/\chi} = \left[\frac{\delta(p - w_W(p))}{\bar{c}_W [q_W(p)]^2}\right]^{1/\chi} = v_W(p). \tag{39}$$

Given the definition of λ,

$$\lambda_E = \int_{b_E}^{\bar{p}_E} v_E(z)\,\gamma_E(z)\,dz,$$

we obtain

$$\lambda_E = \int_{b_E}^{\bar{p}_E} v_E(x)\,\gamma_E(x)\,dx = \int_{b_E/\kappa}^{\bar{p}_E/\kappa} v_E(\kappa y)\,\gamma_E(\kappa y)\,\kappa dy = \int_{b_W}^{\bar{p}_W} v_W(y)\,\gamma_W(y)\,dy = \lambda_W,$$

as claimed, where the second equality holds by a change in variable.

We finally need to focus on the accounting equations, and show that G and F hold as well. Note that $u_W = u_E$ holds trivially, since $\lambda_W = \lambda_E$, $\theta_E = \theta_W$, and $\delta_W = \delta_E$.To verify that the relationship for F holds, we use that

$$\begin{aligned} F_E(\kappa p) &= \frac{\int_{b_E}^{\kappa p} v_E(x)\gamma_E(x)dx}{\int_{b_E}^{\bar{p}_E} v_E(x)\gamma_E(x)dx} \\ &= \frac{\int_{b_E/\kappa}^{p} v_E(\kappa y)\gamma_E(\kappa y)\kappa dy}{\int_{b_E/\kappa}^{\bar{p}_E/\kappa} v_E(\kappa y)\gamma_E(\kappa y)\kappa dy} \\ &= \frac{\int_{b_W}^{p} v_W(y)\gamma_W(y)dy}{\int_{b_W}^{\bar{p}_W} v_W(y)\gamma_W(y)dy} \\ &= F_W(p). \end{aligned}$$

The condition for G can then be verified using the flow equation (35). This concludes the proof. Since we assumed that the W functions are an equilibrium for the West, than the properly defined E functions are an equilibrium for the East.

E.2 Proof of Lemma 2 3

If $b_E = b_W$, then from equation (??) we have that $U_E = U_W$. Therefore, unemployed workers are indifferent between unemployment in either region. It follows from equation (??) that the probability of accepting a job offer when unemployed is equal to $\hat{P}_i(w) = 1$ in both regions. Firms post wages $w \geq b_i$, and the East German firms with $p < b_i$ exit the market and do not post wage offers. From equation (??), the steady-state unemployment ration in a region i is then

$$\frac{u_i}{n_i} = \frac{\delta_i + \theta_i}{\bar{\lambda}_i + \bar{\lambda}_j}. \tag{40}$$

Since $\delta_E = \delta_W$ and $\theta_E = \theta_W$ by assumption, the unemployment to employment ratio is the same in both regions.

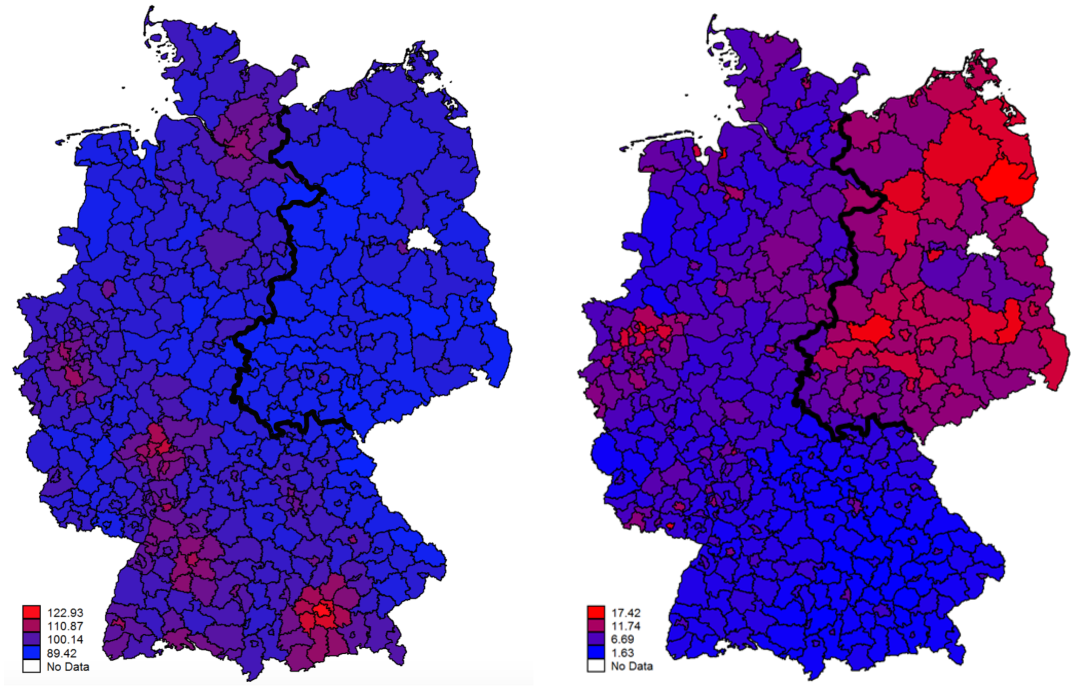
To see that allocational quality is not necessarily the same in both regions, note that since workers are indifferent between being in either region, they will move to any firm that offers them a higher job. Hence, for a firm posting wage w, the hiring probability $h_i(w)$ and the quit probability $q_i(w)$ will be the same in both regions. From equation (??), a firm with the same productivity p will therefore post the same wage w in both regions. However, if the cost of vacancy posting $\bar{c}_i$ differs across regions, then firms of the same productivity level will have a different size in both regions. Furthermore, the lower tail of the East German firms does not post wages since $p < b_E$. Dependent on the shape of the upper tail of the firm productivity distribution, the ratio of the weighted average wage to the unweighted average may either be higher or lower in the East than in the West. Hence, in general, $\rho_E \neq \rho_W$.

F Additional Figures

Figure 14: Price Level and Unemployment

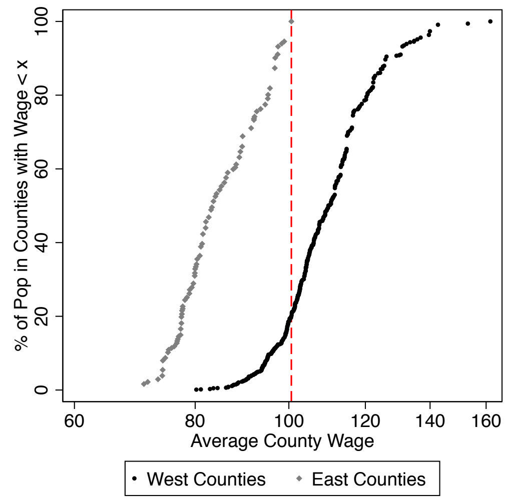
(a) Price Level, 2009

(b) Average Unemployment, 2009-2014

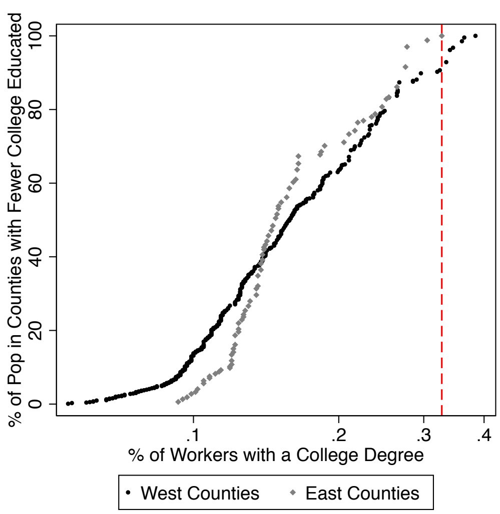


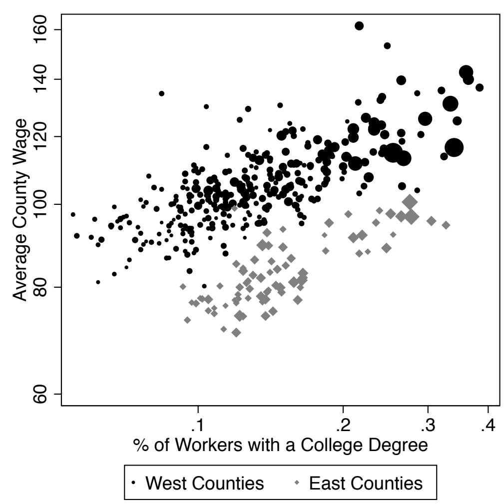
Sources: BBSR, Bundesagentur für Arbeit. Notes: The left figure plots the price level in 2009 for each county. The right figure shows the unemployment rate, calculated as all unemployed workers divided by (unemployed + civilian dependent workers).

Figure 15: Cumulative Distribution Functions of Real Wages in East and West



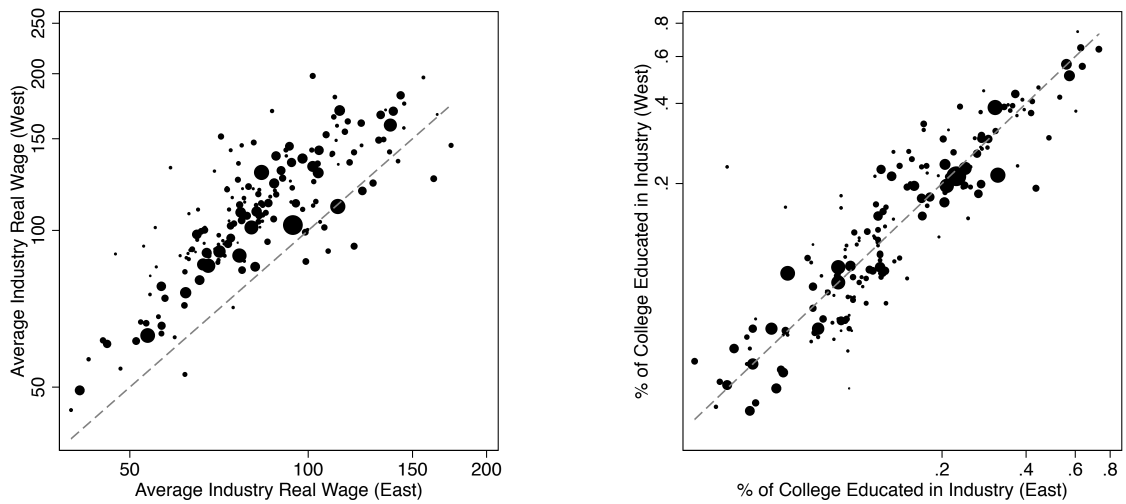
Note: The figure shows the CDF of real wages in East and West German counties. Each dot is a county, where the steepness of the CDF is determined by the share of each region's population captured by the next county. The red-dashed line shows the average real wage of the highest-paying county in East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





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

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. Source: BHP.

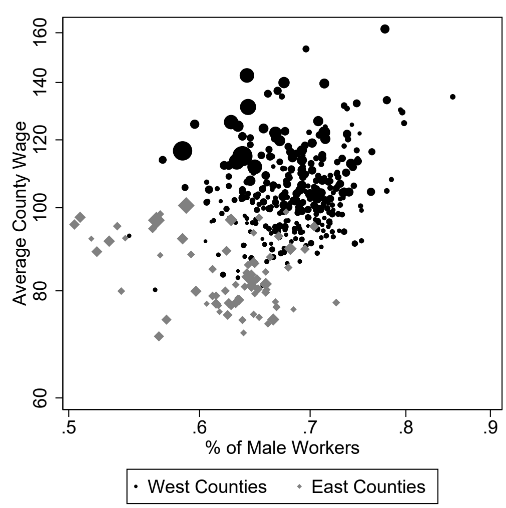


(c) Real Wage Gap by Industry

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

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 16: Real Wage by Share of Males Across Counties

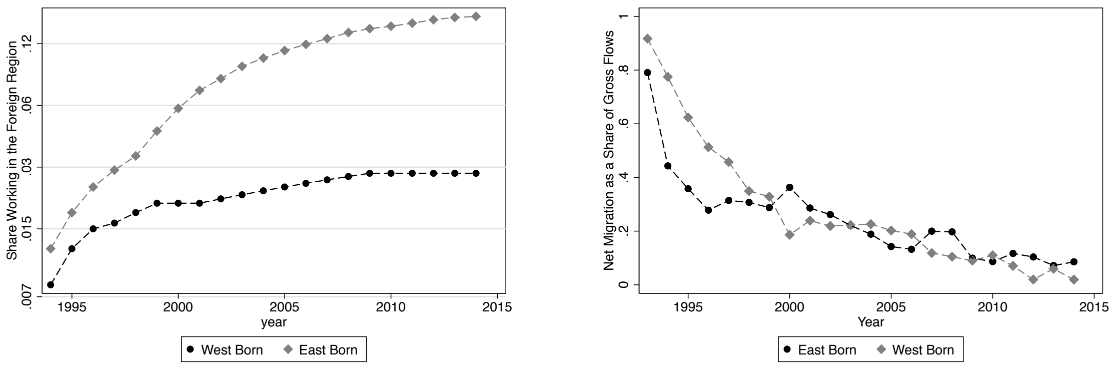


Notes: The figure plots the share of full-time male workers in each county against the average real wage of the county. The size of each dot is determined by the population in each county. Source: BHP.

Figure 17: East-West Mobility over Time

(a) Stock of Workers away from Home Region

(b) Net Flows Across Regions by Home Region

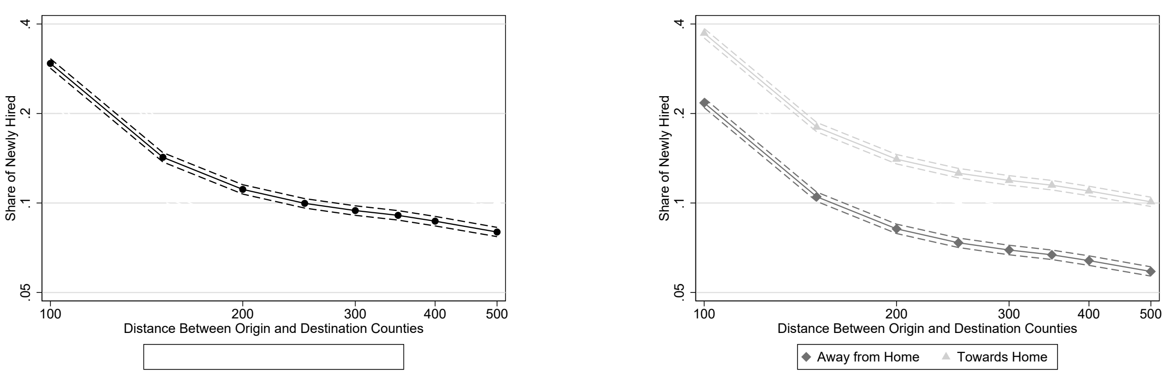


Notes: The left figure plots the share of workers by home region currently working in the other region. Each worker is counted once each year, regardless of the number of spells. The right figure shows the number of workers moving out of their home region minus the number of workers moving back in a given year, divided by the total number of workers moving across regions.

Figure 18: Effect of Distance and Identity on Worker Flows

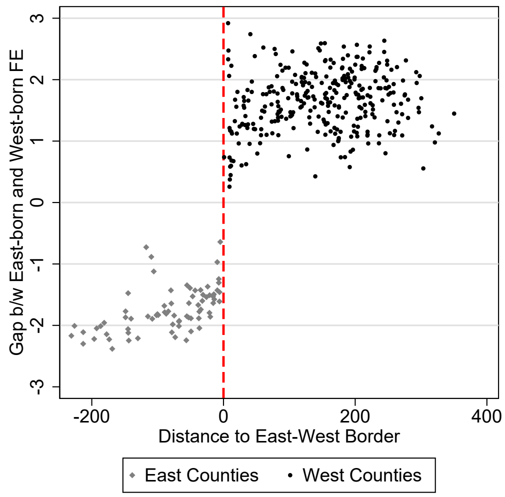
(a) Distance

(b) The Role of Identity



Notes: Left figure presents the distance coefficients from specification (6). We normalize the coefficients so that they sum to 1 including the excluded category, which is up to 50km. Right figure adds β_2 and β_3, respectively, to these coefficients.

Figure 19: Origin FE



Notes: The figure plots the difference between the origin fixed effects for East- and West-born workers obtained from regression (7), 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.

G Additional Tables

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

$\bar{w}_{jt}$	(1)	(2)	(3)
$\mathbb{I}_{j,East}$	$-$**.1600*****	$-$**.1942*****	$-$**.1743*****
	(.0013)	(.0011)	(.0010)
Year FE	Y	Y	Y
Observable controls	–	Y	Y
Industry	–	–	Y
Observations	4,797,798	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: Effect of Birth Location on Real Wage, by Current Location

	Current Region: West				Current Region: East			
w_{itbr}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{I}_i^{East}$	$-$**.1395*****	$-$**.0921*****	$-$**.0473*****	$-$**.0278*****	$-$**.1497*****	$-$**.0272*****	$-$**.0488*****	$-$**.0506*****
	(.0024)	(.0022)	(.0017)	(.0016)	(.0058)	(.0057)	(.0030)	(.0028)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Age/edu/male	–	Y	Y	Y	–	Y	Y	Y
Industry	–	–	Y	Y	–	–	Y	Y
Ind $\times$ county	–	–	–	Y	–	–	–	Y
Observations	5.29m	5.29m	5.29m	5.29m	2.26m	2.26m	2.26m	2.26m

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

Table 12: Effect of Birth Location on Real Wage, Young Individuals (born 1975 or later)

w_{itbr}	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}_i^{East}$	$-\mathbf{.2594}^{***}$	$-\mathbf{.2224}^{***}$	$-\mathbf{.1540}^{***}$	$-\mathbf{.0345}^{***}$	$-\mathbf{.0156}^{***}$
	(.0020)	(.0018)	(.0013)	(.0027)	(.0019)
Year FE	Y	Y	Y	Y	Y
Age/edu/male	–	Y	Y	Y	Y
Industry	–	–	Y	–	–
County	–	–	–	Y	–
Ind × county	–	–	–	–	Y
Observations	3,197,513	3,197,513	3,197,510	3,197,513	3,197,510

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

Table 13: Effect of Birth Location on Real Wage, Middle Aged Individuals (born 1965-1974)

w_{itbr}	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}_i^{East}$	$-\mathbf{.3029}^{***}$	$-\mathbf{.2428}^{***}$	$-\mathbf{.1729}^{***}$	$-\mathbf{.0738}^{***}$	$-\mathbf{.0476}^{***}$
	(.0032)	(.0032)	(.0020)	(.0046)	(.0032)
Year FE	Y	Y	Y	Y	Y
Age/edu/male	–	Y	Y	Y	Y
Industry	–	–	Y	–	–
County	–	–	–	Y	–
Ind × county	–	–	–	–	Y
Observations	1,847,897	1,847,897	1,847,891	1,847,897	1,847,891

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

Table 14: Effect of Birth Location on Real Wage, Older Individuals (born before 1965)

w_{itbr}	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}_i^{East}$	$-\mathbf{.3492}^{***}$	$-\mathbf{.3247}^{***}$	$-\mathbf{.2322}^{***}$	$-\mathbf{.1231}^{***}$	$-\mathbf{.0746}^{***}$
	(.0022)	(.0022)	(.0016)	(.0044)	(.0030)
Year FE	Y	Y	Y	Y	Y
Age/edu/male	–	Y	Y	Y	Y
Industry	–	–	Y	–	–
County	–	–	–	Y	–
Ind × county	–	–	–	–	Y
Observations	2,509,500	2,509,500	2,509,497	2,509,500	2,509,497

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

Table 15: AKM Decomposition by Age Cohort

		Young (born from 1975)		Middle (1965-1974)		Older (before 1965)	
		(1)	(2)	(3)	(4)	(5)	(6)
		$\hat{\beta}$	*s.e.*	$\hat{\beta}$	*s.e.*	$\hat{\beta}$	*s.e.*
(1)	Establishment FE	$-\mathbf{.1310}^{***}$	(.0100)	$-\mathbf{.1342}^{***}$	(.0188)	$-\mathbf{.1644}^{***}$	(.0158)
(2)	Worker FE	$-\mathbf{.0521}^{***}$	(.0013)	$-\mathbf{.1071}^{***}$	(.0016)	$-\mathbf{.1510}^{***}$	(.0012)
(3)	Point estimates on $\mathbb{I}_i^{(b=\text{East};\ r=\text{West})}$	.0311		.0050		.0025	

Notes: $*$, $**$, and $***$ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the establishment level for row (1) and at the individual level for row (2). Row (3) provides the relative comparative advantage of East German workers in the West.

Table 16: 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%

Table 17: Gravity Equation for Sub-Groups

	Males	Females	College	No college	Young	Middle	Older	Non-German	No unemp
$\mathbb{I}^{East}$	**.1642*****	**−.0475*****	**.2435*****	**.1236*****	**−.0249*****	**.3441*****	**.0704*****	**1.0737*****	**.1683*****
	(.0076)	(.0115)	(.0116)	(.0076)	(.0089)	(.0105)	(.0110)	(.0229)	(.0189)
ϕ_{50-100}	**−1.7278*****	**−1.5692*****	**−1.0707*****	**−1.8340*****	**−1.6926*****	**−1.4936*****	**−1.4891*****	**−1.2353*****	**−1.7224*****
	(.0189)	(.0200)	(.0194)	(.0190)	(.0187)	(.0199)	(.0214)	(.0251)	(.0189)
$\phi_{101-150}$	**−2.4143*****	**−2.1287*****	**−1.4762*****	**−2.5640*****	**−2.3488*****	**−2.0042*****	**−1.9746*****	**−1.5205*****	**−2.3939*****
	(.0187)	(.0204)	(.0198)	(.0188)	(.0187)	(.0203)	(.0217)	(.0268)	(.0188)
$\phi_{151-200}$	**−2.6302*****	**−2.2834*****	**−1.5808*****	**−2.7941*****	**−2.5499*****	**−2.1195*****	**−2.1090*****	**−1.5927*****	**−2.6061*****
	(.0187)	(.0207)	(.0201)	(.0189)	(.0187)	(.0205)	(.0221)	(.0278)	(.0188)
$\phi_{201-250}$	**−2.7286*****	**−2.3417*****	**−1.6314*****	**−2.9032*****	**−2.6380*****	**−2.1516*****	**−2.1401*****	**−1.6570*****	**−2.6961*****
	(.0188)	(.0210)	(.0205)	(.0190)	(.0190)	(.0205)	(.0220)	(.0297)	(.0190)
$\phi_{251-300}$	**−2.7754*****	**−2.3650*****	**−1.6535*****	**−2.9452*****	**−2.6725*****	**−2.2042*****	**−2.1523*****	**−1.6502*****	**−2.7442*****
	(.0190)	(.0213)	(.0211)	(.0191)	(.0192)	(.0209)	(.0224)	(.0297)	(.0192)
$\phi_{301-350}$	**−2.8111*****	**−2.3672*****	**−1.6701*****	**−2.9846*****	**−2.7112*****	**−2.1915*****	**−2.1443*****	**−1.6812*****	**−2.7781*****
	(.0193)	(.0219)	(.0219)	(.0194)	(.0194)	(.0216)	(.0232)	(.0299)	(.0195)
$\phi_{351-400}$	**−2.8535*****	**−2.4029*****	**−1.7064*****	**−3.0296*****	**−2.7498*****	**−2.2273*****	**−2.1956*****	**−1.7018*****	**−2.8225*****
	(.0195)	(.0224)	(.0223)	(.0197)	(.0198)	(.0221)	(.0233)	(.0316)	(.0198)
ϕ_{401+}	**−2.9287*****	**−2.4343*****	**−1.7564*****	**−3.1008*****	**−2.8126*****	**−2.2798*****	**−2.1936*****	**−1.7359*****	**−2.8904*****
	(.0191)	(.0213)	(.0211)	(.0191)	(.0192)	(.0210)	(.0225)	(.0292)	(.0192)
$\mathbb{I}^{(R(o)\neq R(d))}$	**.0390*****	.0115	**−.0397*****	**.0478*****	**.0815*****	.0077	−.0130	**.2314*****	**.0281*****
	(.0085)	(.0118)	(.0124)	(.0085)	(.0094)	(.0111)	(.0117)	(.0240)	(.0090)
$\mathbb{I}^{(R(o)=b)}$	**−1.6354*****	**−1.8305*****	**−1.6465*****	**−1.6733*****	**−1.7593*****	**−1.6779*****	**−1.8614*****	**−1.6417*****	**−1.6696*****
	(.0069)	(.0105)	(.0105)	(.0070)	(.0080)	(.0095)	(.0103)	(.0199)	(.0073)
$\mathbb{I}^{(R(d)=b)}$	**.5579*****	**.4525*****	**.3599*****	**.5745*****	**.5785*****	**.4084*****	**.4022*****	**.2733*****	**.5526*****
	(.0070)	(.0100)	(.0107)	(.0069)	(.0078)	(.0097)	(.0102)	(.0216)	(.0074)
Observations	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. 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. Last column excludes all job transitions via unemployment.

Table 18: Extended Gravity Equation

	(1)	(2)	(3)
	Birth-specific FE	In Home	Not in Home
	Effect of Distance Within Region		
ϕ_{50-100}	$\mathbf{-1.7829}^{***}$	$\mathbf{-2.22}^{***}$	$\mathbf{-1.355}^{***}$
	(0.0189)	(0.023)	(0.026)
$\phi_{101-150}$	$\mathbf{-2.5068}^{***}$	$\mathbf{-3.057}^{***}$	$\mathbf{-1.763}^{***}$
	(0.0186)	(0.022)	(0.026)
$\phi_{151-200}$	$\mathbf{-2.7679}^{***}$	$\mathbf{-3.352}^{***}$	$\mathbf{-1.875}^{***}$
	(0.0185)	(0.022)	(0.025)
$\phi_{201-250}$	$\mathbf{-2.8884}^{***}$	$\mathbf{-3.484}^{***}$	$\mathbf{-1.937}^{***}$
	(0.0186)	(0.022)	(0.026)
$\phi_{251-300}$	$\mathbf{-2.9484}^{***}$	$\mathbf{-3.551}^{***}$	$\mathbf{-2.000}^{***}$
	(0.0188)	(0.023)	(0.026)
$\phi_{301-350}$	$\mathbf{-2.9964}^{***}$	$\mathbf{-3.596}^{***}$	$\mathbf{-2.050}^{***}$
	(0.0190)	(0.023)	(0.026)
$\phi_{351-400}$	$\mathbf{-3.0489}^{***}$	$\mathbf{-3.653}^{***}$	$\mathbf{-2.083}^{***}$
	(0.0192)	(0.023)	(0.026)
ϕ_{401+}	$\mathbf{-3.1502}^{***}$	$\mathbf{-3.733}^{***}$	$\mathbf{-2.195}^{***}$
	(0.0189)	(0.022)	(0.026)
	Effect of Distance Across Regions		
ϕ_{1-100}	$-.008$	$\mathbf{-.405}^{***}$	$\mathbf{.105}^{***}$
	(0.010)	(0.0105)	(0.016)
$\phi_{101-150}$	$\mathbf{.0412}^{***}$	$\mathbf{-.425}^{***}$	$\mathbf{.348}^{***}$
	(0.0146)	(0.018)	(0.022)
$\phi_{151-200}$	$\mathbf{.0741}^{***}$	$\mathbf{-.584}^{***}$	$\mathbf{.556}^{***}$
	(0.0152)	(0.019)	(0.022)
ϕ_{201+}	$\mathbf{.1405}^{***}$	$\mathbf{-.471}^{***}$	$\mathbf{.502}^{***}$
	(0.0151)	(0.019)	(0.022)
Observations	94,546	2,509,500	2,509,497

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 point estimates with home region specific fixed effects. In columns (2) and (3), we return to fixed effects that do not depend on the home region as in the baseline, but instead study separately workers that are currently in their home region and those that are not.

Table 19: 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*****	**.3356*****	**.0229*****	**.0459*****
		(.0012)	(.0012)	(.0016)	(.0019)	(.0150)	(.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.

Table 20: Wage Gains for Sub-Groups (Benchmark Specification)

Δw_{it}	Males	Females	College	No college	Young	Middle	Older	Non-German
				Migration				
$d_{it}^{EW,W,m}$	**.1516*****	**.2429*****	**.2281*****	**.2026*****	**.2300*****	**.1569*****	**.1182*****	**.1847*****
	(.0258)	(.0361)	(.0286)	(.0296)	(.0291)	(.0381)	(.0458)	(.0665)
$d_{it}^{WE,W,m}$	**.1616*****	**.2750*****	**.4793*****	**.0573***	**.3183*****	.0729	**−.0955***	**.2336*****
	(.0317)	(.0433)	(.0432)	(.0298)	(.0337)	(.0449)	(.0555)	(.0834)
$d_{it}^{EW,E,m}$	**.3041*****	**.4608*****	**.5890*****	**.3186*****	**.4202*****	**.1953*****	**.1044*****	**.1800*****
	(.0147)	(.0240)	(.0307)	(.0137)	(.0152)	(.0265)	(.0294)	(.0409)
$d_{it}^{WE,E,m}$	.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				
$d_{it}^{EW,W,c}$	**.1110*****	**.1939*****	**.2594*****	**.1305*****	**.1891*****	**.1232*****	**.0718*****	**.1453*****
	(.0091)	(.0230)	(.0190)	(.0096)	(.0136)	(.0160)	(.0149)	(.0343)
$d_{it}^{WE,W,c}$	**.0900*****	**.1554*****	**.2660*****	**.0945*****	**.2068*****	**.0447*****	**.0320***	**.1638*****
	(.0102)	(.0264)	(.0239)	(.0106)	(.0155)	(.0184)	(.0165)	(.0402)
$d_{it}^{EW,E,c}$	**.1321*****	**.2070*****	**.3051*****	**.1525*****	**.2069*****	**.1166*****	**.0719*****	**.0810***
	(.0063)	(.0130)	(.0177)	(.0060)	(.0079)	(.0123)	(.0099)	(.0462)
$d_{it}^{WE,E,c}$	**.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
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.

Table 21: Wage Gains Robustness

	(1)	(2)	(3)	(4)	(5)
	Benchmark specification				
Δw_{it}	Lag time	≤2 mths	≥150km	≥100km	Any move
	Migration				
$d_{it}^{EW,W,m}$	**.0737*****	**.1110*****	**.1466*****	**.1482*****	**.1560*****
	(.0210)	(.0204)	(.0137)	(.0135)	(.0120)
$d_{it}^{WE,W,m}$	−.0101	−.0189	**.1712*****	**.1627*****	**.1526*****
	(.0248)	(.0233)	(.0131)	(.0126)	(.0113)
$d_{it}^{EW,E,m}$	**.1903*****	**.1296*****	**.2066*****	**.2019*****	**.2058*****
	(.0122)	(.0099)	(.0066)	(.0063)	(.0056)
$d_{it}^{WE,E,m}$	**−.0772*****	**−.0429*****	**.0390*****	**.0415*****	**.0448*****
	(.0142)	(.0132)	(.0129)	(.0126)	(.0122)
DiD Migr	−.184	−.043	−.192	−.175	−.158
	Commuting				
$d_{it}^{EW,W,c}$	**.0493*****	**.0639*****	**.1427*****	**.1415*****	**.1366*****
	(.0085)	(.0088)	(.0096)	(.0097)	(.0103)
$d_{it}^{WE,W,c}$	.0097	**.0246****	**.0765*****	**.0748*****	**.0655*****
	(.0097)	(.0103)	(.0120)	(.0125)	(.0148)
$d_{it}^{EW,E,c}\mathbb{I}_i^{East}$	**.0667*****	**.0806*****	**.1975*****	**.2103*****	**.1783*****
	(.0056)	(.0055)	(.0091)	(.0103)	(.0190)
$d_{it}^{WE,E,c}\mathbb{I}_i^{East}$	−.0044	**.0362*****	**.0872*****	**.0866*****	**.0861*****
	(.0057)	(.0056)	(.0058)	(.0058)	(.0058)
DiD Comm	−.031	−.005	−.044	−.057	−.021
Year FE	Y	Y	Y	Y	Y
Indiv. controls	Y	Y	Y	Y	Y
Mobility	Y	Y	Y	Y	Y
Observations	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) adds to the benchmark regression a control for the number of months between job spells. Column (2) drops all job switches where more than two months elapse between jobs.