Spatial Wage Gaps and Frictional Labor Markets

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Abstract

We develop a job-ladder model with labor reallocation across firms and space, which we design
to leverage matched employer-employee data to study differences in wages and labor productivity
across regions. We apply our framework to data from Germany: twenty-five years after the
reunification, real wages in the East are still 26 percent lower than those in the West. We find that
60 percent of the wage gap is due to labor being paid a higher wage per efficiency unit in West
Germany, and quantify three distinct barriers that prevent East Germans from migrating west to
obtain a higher wage: migration costs, workers' preferences to live in their home region, and more
frequent job opportunities received from home. Interpreting the data as a frictional labor market,
we estimate that these spatial barriers to mobility are small, which implies that the spatial
misallocation of workers between East and West Germany has at most moderate aggregate
effects.

Key words: employment, aggregate labor productivity, labor mobility, migration

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1   Introduction

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

In this paper, we revisit these questions in the context of Germany. Germany is a natural setting since it exhibits a persistent 26% wage gap, in real terms, between East and West Germany, which is sharply delineated by the former border, as shown in Figure 1. We analyze the origins of the wage gap using matched employer-employee data, which we interpret through the lens of a novel model which allows labor to reallocate both across firms and across space.

Our paper shows that location matters: more than 60% of the East-West wage gap is due to regional characteristics rather than worker composition, with labor being significantly more productive in the West. We therefore investigate what barriers prevent East German workers from migrating to West Germany. Our data, interpreted through the lens of our model, allow us to distinguish between four possible explanations: differences between East and West Germans in skills, preferences, or opportunities; and migration costs. We find that three of the barriers are jointly responsible for the lack of migration: first, workers have a preference for their home region: individuals value one dollar earned while working away from their home region as 95 cents earned at home. This wedge amounts to a yearly cost of approximately $1,500. Second, workers receive most of their job offers from the region in which they are currently working. For example, an East-born individual working in the East receives only about one in twenty job offers from the West. Finally, moving between regions entails a one time cost equal to 4% of an individual's life-time earnings, or approximately $25,000. The estimated barriers are significantly smaller than previous estimates in the literature.[2] As a result, the implied costs of these spatial barriers due to aggregate misallocation are relatively modest. For example, removing the migration cost would increase GDP by only 0.5% and the aggregate wage by 0.45%. It would generate even smaller welfare gains since workers migrate more and therefore live more frequently away from their home region.

Both matched employer-employee data and a model with labor reallocation across firms are crucial for our analysis. On the one hand, matched data enable us to control for unobserved heterogeneity across workers. This feature allows us to isolate the part of the wage gap that is due to regional characteristics. On the other hand, the structure of our model, once brought to our data, allows us to estimate workers' home region preferences and migration costs using the observed wage gains from movers across regions, rather than worker flows, as in previous work. Our approach has two key features:

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

[2] For example, Kennan and Walker (2011) find, examining inter-state migration of white males in the United States, that the moving cost for the average mover is $310,000 (rather than $25,000 for moves between East and West Germany in our work) and that the home premium corresponds to an yearly wage increase of $23,000 (rather than $1,500).

Figure 1: Average Real Daily Wage, 2009-2014
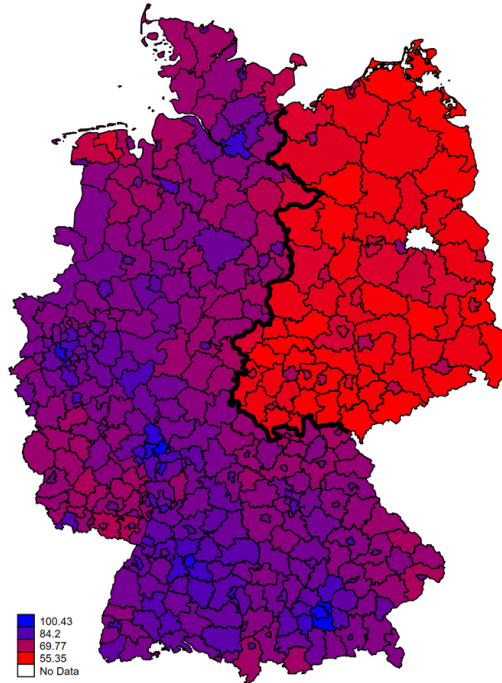
Notes: Average daily wages are obtained from a 50% random sample of establishments via the Establishment History Panel (BHP) of the Institute for Employment Research (IAB). Real wages are expressed in 2007 euros valued in Bonn, the former capital of West Germany, using county-specific price indices from the Federal Institute for Building, Urban Affairs and Spatial Development (BBSR) in 2007, which are written forward in time using state-level price deflators from the Statistical Offices of the States. Former East-West border is drawn in black for clarification, there is no border today.

i) using matched data allows us to benchmark moves across space against moves across firms within the same location, and thus to separate the part of the wage gain that is due to the "spatial" move from the part that is due to the worker's movement up the job ladder; and ii) using a search model allows us to separate the lack of opportunities to migrate, or the number of offers received, from the cost of migration, which affects the share of offers that are accepted.

Our paper consists of three main sections. First, we document three stylized facts about the regional wage gap. Second, we develop a model with worker reallocation across space and across firms to interpret our findings. Finally, we estimate the model quantitatively.

Our empirical work combines two administrative datasets from the German Federal Employment Agency. Our main dataset is matched employer-employee data from the LIAB dataset, which records the entire employment history for more than one million individuals with characteristics of the establishments they work for, for the period 1992-2014. Our second dataset is establishment-level data from the Establishment History Panel (BHP), which provides additional information for half of all establishments in Germany.

We establish three stylized facts. First, we show that the real wage gap between East and West Germany is persistent, and not driven by observables such as industry, education, or gender differences. Second, workers obtain large wage gains when moving from East to West, and these gains are

asymmetric: East-born workers obtain significantly higher average wage gains than West-born workers when making a move from East to West, while the reverse holds for West to East moves. This result suggests that workers need to be compensated to leave their home region. Third, we show that mobility of workers across regions is in fact high, thus suggesting that moving costs might be small. However, even conditional on distance and current location, workers are relatively more likely to move towards their home region, raising the possibility that they receive more job offers from there.

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

The model provides guidance on how matched-employer employee data can be used to understand the origins of the spatial wage gap. First, the model delivers an AKM type regression, which directly pins down – without the need to estimate the model – the average skills of East- and West-born workers. East-born workers are paid a 10% lower wage than West-born ones irrespective of the establishment they work for, accounting for nearly 40% of the East-West wage gap. The remaining part of the gap is due to establishment characteristics, raising the question of what frictions prevent workers from migrating. From the AKM regression, we do not find a relative skill disadvantage of East-born workers in the West. While all other parameters are jointly estimated, the model provides exact decompositions of workers' wage gains from job-to-job switches and of workers' flows across jobs, which provide intuition for how these parameters can be identified. Specifically, if the migration cost is symmetric and identical for all worker types, as is common in economic geography models, then workers' preferences for a given region can be identified by comparing the wage gains of East- and West-born workers making the same job switch across regions. Similarly, the migration cost is identified from the average wage gains of workers that move between East and West Germany. Finally, given workers' preferences and migration costs, and given the structure of the model, any deviation of the flows of workers between regions from the model-implied flows must be due to differences in opportunities.

We estimate the model via simulated method of moments, and show that preferences, opportunities, and migration costs all play a role in supporting the persistent divide. The analysis yields three novel insights. First, we show that a large regional wage gap can be supported in equilibrium by relatively

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small migration frictions, given a frictional labor market and productivity differences across regions. Second, we argue that it is important to distinguish between different spatial frictions, which have significantly different aggregate implications. For example, eliminating the migration cost while keeping the home preference has comparatively little effect on regional GDP in the long run, since workers return home easily. On the other hand, eliminating the preference while keeping the migration cost leads in the long run to significant GDP gains, since eventually most workers will receive a good enough job offer to permanently relocate. Finally, we argue that it cannot be concluded from a lack of flows across regions that the labor market is not integrated. In the example of Germany, workers in fact receive many job offers from the other region. However, they choose not to accept them.

In the final part of the paper, we shed further light on the mechanism driving this home bias. We find that individuals are more likely to move back to their home region after the birth of a child, indicating that they may seek help with childcare from family members. Moreover, 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 although individuals are strongly attached to their home state, there is a significant additional effect working through ties to the overall birth region (East or West).

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 homogeneous 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 heterogeneous 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).[3] 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 contribution is to unpack spatial frictions 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,[4] and we show that they are crucial to distinguish spatial frictions from the general reallocation frictions across firms, which are the focus of

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

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

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.

Two recent papers have studied reallocation of labor across space or sectors in a frictional labor market. Schmutz and Sidibé (2018) build a partial equilibrium model where identical workers receive job offers both from their current and from other locations. Similar to our work, this paper estimates small migration costs. However, due to the partial equilibrium assumption, the authors cannot study the aggregate effects of spatial frictions. Their paper also does not allow for worker heterogeneity, which turns out to be relevant since workers have a preference for their home region. Meghir, Narita, and Robin (2015) develop a general equilibrium model with two sectors to study the allocation of labor between the formal and informal sector in Brazil. They also assume workers are identical, and do not allow for a migration cost across sectors.

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, 2006), Fuchs-Schündeln, Krueger, and Sommer (2010)). Uhlig (2006, 2008) shows that the persistent East-West wage gap can be consistent with network externalities, which discourage firms from moving to the East. In our model, we take as exogenously given the distribution of firms in each region and do not explicitly model the source of the productivity differences across regions. Instead, we use matched employer-employee data to estimate the roles of various migration frictions in a unified framework.

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

2 Data

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

Our second, most important dataset are 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 socioeconomic characteristics of all individuals that were employed subject to social security or received social security benefits since 1993. These data are linked to information about approximately 400,000 establishments at which these individuals work from the BHP. For each individual in the sample, the data provide the entire employment history for the period 1993-2014, including unemployment periods. Each observation is an employment or unemployment spell, with exact beginning and end dates within a given year. A new spell is recorded each time an individual's employment status changes, for example due to a change in job, wage, or employment status. For individuals that do not change employment status, one spell is recorded for the entire year. Variables include the worker's establishment's location at the county level, the worker's daily wage, education, year of birth, and occupation. The data also contain the county of residence of the individual, since 1999. In contrast to the other variables, which are newly reported at each spell, the location of residence is only collected, for employed workers, at the end of each year and then added to all observations of that year, while for unemployed workers it is collected at the beginning of an unemployment spell.

The third dataset used is the German Socio-Economic Panel (SOEP), a longitudinal annual survey of around 30,000 individuals in Germany since 1984. The SOEP provides information about an individual's employment, family, living conditions, and education history. We will use the SOEP to further study the effects of an individual's birth location, which can reasonably be infered for two sub-samples of the data. First, the first wave of individuals in the SOEP drawn in 1984 covered only West German individuals, while a wave in 1990 covered only East German individuals. For these waves the birth location is thus known with certainty. We will refer to individuals from these waves that are still in the labor force in 2009-2014 as the "Old SOEP Sample". Second, for individuals that entered the survey

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

while they were still in their childhood, the data contain information on the location of individuals' preschool, primary school, or secondary school, which we will assume is identical to their birth location. We refer to such individuals who began high-school after the reunification and are not in the Old Sample as the "Young SOEP Sample".

Our fourth dataset is information on cost of living differences across German counties from the Federal Institute for Building, Urban Affairs and Spatial Development (BBSR (2009)). The BBSR conducted a study assessing regional price variation in 2007 across 393 German micro regions covering all of Germany that correspond to counties or slightly larger unions of counties.[6] The data cover about two thirds of the consumption basket, including housing rents, food, durables, holidays, and utilities. Figure 13a in Appendix D shows the map of county-level price levels. East Germany has a 7% lower population-weighted average price level.

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

3 Empirical Evidence of the Enduring Divide

We use our rich datasets to document three facts. First, Fact 1 shows that there is a persistent real wage gap between East and West Germany, which is not driven by observables such as industry, education, or gender differences. We then show that the three classic hypotheses formulated by the literature to explain real wage gaps − (i) wages are higher in one region due to higher unobserved ability of workers and spatial sorting, (ii) wages are higher in one region as compensation for disamenities, and (iii) mobility barriers prevent reallocation − are in our context, at best, incomplete. Specifically, Fact 2 documents that workers obtain large wage gains when moving from East to West, thus suggesting that a simple sorting explanation is not at play. Furthermore, these wage gains are asymmetric across worker types, and thus unlikely to be the reflection of some general higher amenity of working in the East. Fact 3 highlights that there is in fact high mobility of workers across regions. We analyze the data through a gravity framework and show that individuals are, conditional on distance, more attracted to their home region than to the other region. These results indicate that only a migration cost explanation is also not appealing, but instead suggest that individuals are biased towards their home region, for example due to their skills, preferences, or opportunities. We structurally interpret our findings through a model

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

Figure 2: East-West Real Wage Gap
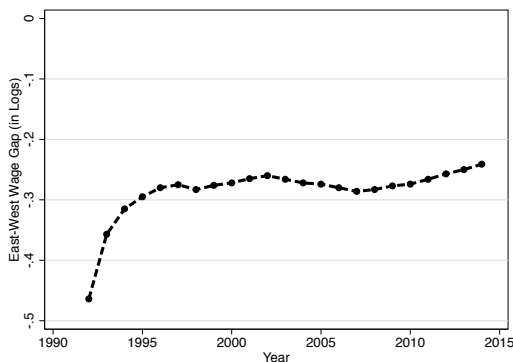
in Section 4 to quantify the importance of these sources of home bias.

Fact 1: Persistent Wage Gap, not due to Observables

We first show that despite the absence of a physical or legal border or language difference between East and West Germany since the reunification in 1990, a sizable and persistent real wage gap remains that is not driven by observables.[7] Figure 1 plots the average daily wage from the BHP, adjusted for cost-of-living differences from the BBSR survey, for each county in Germany.[8] The large wage gap is not driven by a few outlier counties: Figure 14 in Appendix D 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 and persistence of the regional wage gap, we run in the BHP establishment-level regressions of the form

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

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.[9] In a first step, we confirm the persistence of the real wage gap by running regression (1) without controls separately for each year in the data, and plot the resulting time series of coefficients γ_t in Figure 2. We find that the real wage gap has been closing very slowly since the mid-1990s, and remains at around 25%.[10]

We next pool the data for our core sample period (2009-2014) and add successively more controls

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

[8]Figure 13b in Appendix D shows that there is also a sharp difference in unemployment across the two regions.

[9]Table 1 in Appendix E provides the unweighted estimates.

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

Table 1: Effect of Region on Real Wage

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

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

to show that the wage gap is not driven by observable worker characteristics or industry heterogeneity. Table 1 presents the estimates for γ from this pooled regression, where we weigh establishments by the number of workers. Column (1) shows that the unconditional wage gap for our core period is 26%. In column (2), we additionally control for the establishment's average share of male workers to account for gender differences and the share of workers with a college degree, and in column (3) we further add controls for the share of workers that are older than 55 and the share of workers that are younger than 30 to control for age differences, as well as the log of establishment size. With these controls the gap narrows slightly, to 25%. Finally, column (4) of Table 1 includes 3-digit industry fixed effects to control for differences in industry structure, which narrows the gap slightly further. Overall, about 80% of the real wage gap is not explained by these observables. We provide more information on the college, gender, and industry controls in Figures 15a-15 in Appendix D, where we show that the share of college educated individuals is very similar in East and West, that the wage gap exists broadly and is roughly constant across all industries, and that the wage gap holds across counties with different gender composition or education. Appendix B.2 highlights that there is no clear gap in the average tax rate between East and West Germany.

Fact 2: Large Wage Gains for Moves Away from Home

We next show that a given worker obtains large wage gains when he leaves his home region, even after controlling for observable and unobservable heterogeneity. For this analysis and for the remainder of the paper, we assign individuals to a "home region", either East or West Germany, and compare individuals with different home region in 2009-2014. Since the social security data only provides labor market information, we classify individuals as East German (West German) if at the first time they appear in our entire dataset since 1993, in employment or unemployed, their location of residence is in the East (West). Since the residence location is unavailable prior to 1999, we use the workers' first job's establishment location for those years.

We use survey data from the SOEP to validate our measure of an individual's home region. Using

the "Old Sample", we impute a home region in the same way as in the LIAB, and compare it to workers' true home region as reported in the survey. As shown in Table 9 in Appendix E, we find that the imputed home region corresponds to workers' true birth region for 88% of workers born in East Germany and 99% of workers born in the West. In the "Young Sample", where we do not observe the birth region directly, the imputed home region matches the region in which we observe the earliest non-tertiary schooling for an individual in 92% and 99% of cases, respectively. We find no evidence that our misclassification of some workers quantitatively alters the wage gap. In Appendix E, Table 10 compares the wage gap in the SOEP between individuals classified as East and West German under our imputation to the wage gap calculated with the true birth region, and shows that the wage gap is similar under both definitions. Given this evidence, we will also interpret workers' home region as their "birth" region going forward.

To study individuals' wage gains as they move jobs, we define job switches as cases where a worker changes jobs between two establishments without an intermittent unemployment spell.[11] For cross-region switches, we define two types of moves: migration and commuting. In the former, the worker changes her job and residence location, which we observe, while in the latter only the job location is changed. The distinction is useful because we expect that workers that commute to a new job are paid a smaller wage premium than workers that also have to move their residence. Since the residence location is only reported at the end of each year, we define migration as an instance where a worker switched jobs between regions and lived in the region of her first job in the year prior to the move and in the region of the second job at the end of the year of the move. The remaining cases are defined as commuting. We analyze alternative definitions below. Let d_{it}^x be a dummy for a job move of type $x \in \mathbb{X}$, where $\mathbb{X} = \{EW_m, EW_c, WE_m, WE_c, EE, WW\}$ captures moves from East to West via migration and commuting, West to East via migration and commuting, within-East, and within-West, respectively. To visualize an individual's wage dynamics around the time of a job-to-job move, we run local projections of the form

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

where $\Delta w_{i\tau}$ is the change in an individual's average annual wage between year $\tau \in \{t-3, ..., t+5\}$ and the previous year, $\mathbb{I}_i^{East}$ is a dummy for whether an individual's home region is East Germany, X_{it} is a set of time-varying controls, and ρ_i are individual fixed effects.[12] The controls X_{it} include the current work region and its interaction with the home region, distance dummies since moves further away could lead to higher wage gains, the total number of past job-to-job switches, age controls, and

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

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

Figure 3: Wage Gains from Cross-Region Moves

(a) East to West Move   (b) West to East Move
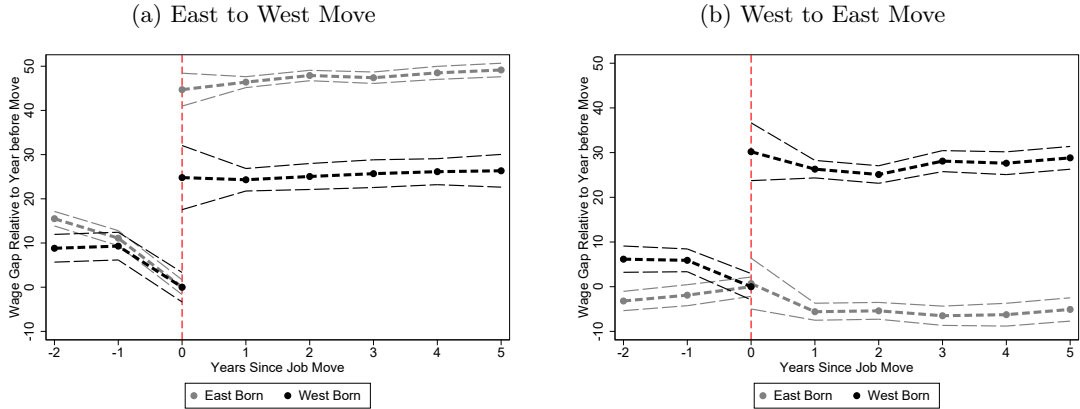
year fixed effects. The coefficients β_x^{West} and β_x^{East} capture the real wage gains from making a job-to-job transition relative to the wage growth obtained by staying at the same establishment, which is the omitted category. To trace out the wage dynamics over multiple years, we run the regression on an extended period from 2002-2014.

Figure 3a plots the estimated wages that are obtained from the migration coefficients $\beta_{EW,m}^{West}(\tau)$ and $\beta_{EW,m}^{East}(\tau)$, translated into levels, where we normalize the year of the migration event to zero. Figure 3b presents the wage gains for West-to-East migration. The two figures show 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 East-to-West, on impact East-born workers receive a 45% wage increase relative to their average wage growth within an establishment, while West-born workers obtain only 25%. In comparison, East-born workers obtain only a 1% increase on impact when they move West-to-East, while West-born workers experience a 30% wage increase.

A tempting conclusion based on these findings would be that workers face large spatial frictions, which they have to be compensated for by wage gains. However, this conclusion is flawed, since movers must receive a job offer to change jobs and are therefore selected. To make this point clearer, in Figures 4a-4b we plot the estimated wage gains for within-region job-to-job switches from regression (2) against the wage gains from migrating across regions. On average, East Germans obtain an 11% wage increase when moving within the East, while West workers receive a wage gain of about 20% when switching jobs within the West. We will need to benchmark the cross-regional wage gains with these within-region gains to obtain the spatial component of wage gains.

We present the full estimates from specification (2) for $\tau = 0$ in Table 11 in Appendix E, and note that the wage gains from commuting are smaller than those for migration but follow a similar ordering, as expected. We then perform several robustness checks, which are run on the core sample period. First, we analyze whether our results are sensitive to our definition of job switches by adding to the benchmark regression a control for the number of months passed between subsequent employment spells, to capture that workers may be non-employed between jobs. Alternatively, we define job switches

Figure 4: Wage Gains from Within-Region Moves

(a) East to West Move   (b) West to East Move
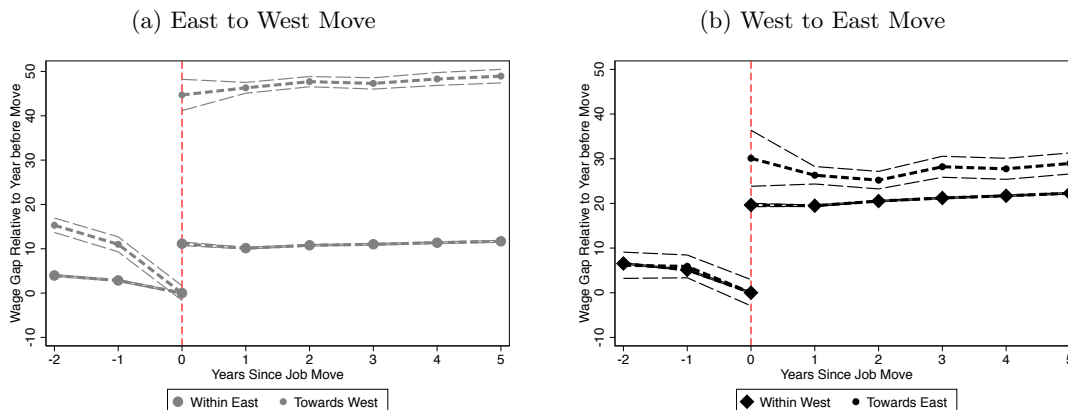
only as cases where the new job starts within two months of the old one. Columns (1)-(2) of Table 11 in Appendix E show that our findings are robust to these alternatives.[13] Second, we study different definitions of migration. Even though some job switchers do not change their reported residence, they 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 11 show that the wage gain of commuters falls slightly, as expected, but our overall conclusions remain unchanged.

Table 12 in Appendix E presents benchmark estimates for different sub-groups and shows that the results are consistent, though we do not find home bias for older workers.[14] We also do not find home bias for non-German immigrants, for whom we define the home region in the same way as for German natives as their first region of residence in Germany. This finding makes sense since these workers are presumably less attached to specific regions in Germany.

Fact 3: High Mobility across Regions but Flows are Distorted

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

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

[14]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.

Table 2: 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

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

To demonstrate that workers are very mobile, Table 2 presents some cross-regional mobility statistics for our core sample of workers. The first row shows that during our core period 2009-2014, 3% of employment spells by West-born workers and 16% of spells by East-born workers are not in their home region. Overall, of the workers in our sample, 8% of 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 to a job in their home region, and workers on average spend only 3 years employed in the other region (row 4). The final three rows of Table 2 present some characteristics of workers that never left their home region, have moved to the other region, and that have returned. While movers are slightly more likely to be college-educated than stayers, less educated workers are also very likely to move, comprising about three quarters of all movers from the East.[15]Table 13 in Appendix E shows the statistics split by whether a worker moved in the early or in the late part of the sample, and shows that a substantial fraction of movers has returned home in both samples. As a result of the significant return migration, while the net outflows of East workers to the West were very large in the 1990s, in our core period they are very minor (Figure 16a in Appendix D) and the increase in the total stock of workers away from their home region has gradually leveled off (Figure 16b in Appendix D).

To show more formally that workers' mobility is biased towards their home region, we estimate a gravity equation for workers' flows between counties. Gravity equations are frequently used in international trade to explain trade flows (e.g., Eaton and Kortum (2002), Chaney (2008)). Here, we

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

apply these techniques to the flows of workers. We will show that geographic barriers along the former East-West border do not play a role in explaining mobility across the two regions, while a worker's type (East or West German) does.

Let $n_{o,d,t}^h$ be the total number of workers with home region h that were in a job in county o in year $t-1$ and are in a new job in county d in year t. These workers may or may not have been unemployed in between jobs.[16] We compute the share of these job-to-job switchers from county o moving to county d (which can be equal to o) across all years in our core period as

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

where $\mathbb{D}$ is the set of all the 402 counties in both East and West Germany.[17] We use these shares to fit the gravity equation

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

where δ_o^h and γ_d^h are county of origin and destination fixed effects, respectively, which differ by workers' home region, $D_{x,o,d}$ are dummies for buckets of distance traveled between origin and destination, $D_{y,o}$ are dummies for buckets of the distance between the origin county and the East-West border, and $\xi_{o,d}$ is a dummy that is equal to one if the move between o and d is a cross-region move. The set of buckets $\mathbb{X}$ contains 50km intervals from 50km-99km onward to 350km-399km, and an eighth group for counties that are further than 399 km apart. The set of buckets $\mathbb{Y}$ contains the intervals 1km-99km, 100-149km, 150-199km, and more than 199km.[18]

The regression investigates three channels that could affect worker flows. First, the dummies $D_{x,o,d}$ capture the role of distance. If workers are less likely to move between counties that are further apart, then the coefficients ϕ_x should decline with distance. Second, the term involving the cross-border dummy $\xi_{o,d}$ reflects the role of geographical barriers affecting mobility between East and West Germany. If all workers, regardless of their home region, are less likely to make a job switch if that switch involves moving between East and West Germany, then the coefficients ψ_y should be negative. We refer to this effect as "geographical border effect". We allow cross-region mobility to vary with the distance of the worker's current location from the border to allow for the possibility that workers in origin counties closer to the border find it easier to cross. Finally, the home-region specific fixed effects δ_o^h and γ_d^h capture the fact that some counties may be more attractive than others to workers of home region h, for example due to preferences, comparative advantage, or possibly due to a social network

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[16]We also computed the results excluding all workers with intermittent unemployment. The results are similar, see the last column of Table 15 in Appendix E.

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

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

Figure 5: Geography versus Identity

(a) Geography

(b) Identity: Destination FE
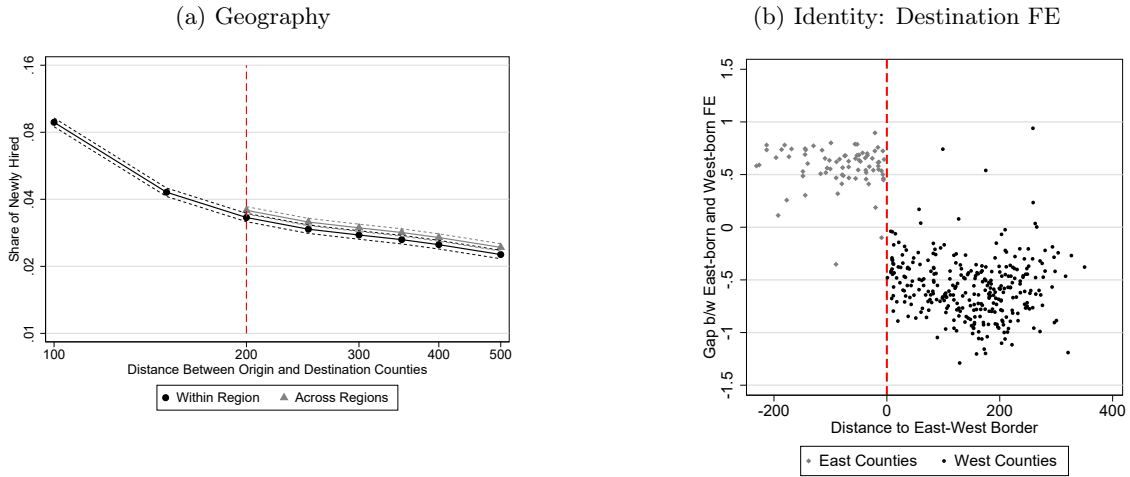
that allows them to find job opportunities. For example, if γ_d^h is high for a destination then a high share of workers of type h move into that county regardless of their origin location and regardless of whether these workers have to cross the East-West border. To the extent that these fixed effects differ systematically between an East and a West German workers for counties located in a given region, the two types of workers have a different valuation for being in that region. We refer to this channel as "identity border effect".

We present the full list of estimated coefficients of regression (3) in Table 14 in Appendix E, and present here only the key coefficients. In Figure 5a, the black line plots the distance coefficients ϕ_x, which we re-normalize into interpretable shares of switchers. Workers are less likely to move to counties that are further away, as expected. The gray line plots, for an average county situated at 200 km from the regional border, the cross-border flows at distances $x \in \mathbb{X}$ for $x \geq 200$ (the coefficients $\phi_x + \psi_y$), taking the origin and destination effects as constant.[19] The lines are almost on top of each other. Thus, conditional on distance and fixed effects, we do not find a role for the geographical border effect.

Finally, Figure 5b shows that there is a strong identity border effect. For each county, we compute the difference between the destination fixed effect for East- and West-born workers. We then plot the resulting differences as a function of the county distance to the East-West border, defined so that East counties have negative distance.[20] The figure shows that East individuals have significantly higher destination fixed effects for the East, indicating that they are more likely to move to counties in the East than West workers regardless of distance and whether they have to cross the border. Conversely,

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

[20]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.

East-born workers are less likely to move to counties in the West. Figure 17 in Appendix D presents the origin fixed effects, and highlights that workers are also less likely to move out of counties in their home region. The results imply that both East and West workers have a strong "home bias".

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

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

where $\mathbb{K} = \{R(o) \neq R(d), R(o) = h, R(d) = h\}$ and $\mathbb{I}^{East}$ is equal to one if a worker's home region is East Germany. The term $\mathbb{I}^{(R(o) \neq R(d))}$ is a dummy for cross-region moves, which captures the geographical border effect. The terms $\mathbb{I}^{(R(o)=h)}$ and $\mathbb{I}^{(R(d)=h)}$ are dummies that equal one when the origin county and the destination county, respectively, are equal to the home region, and capture the identity border effect. If the identity of the worker does not matter, then the coefficients on these latter two dummies should be equal to zero. Table 15 in Appendix E presents the coefficients for different sub-groups of the population and shows that while the attachment to the home region is weaker for skilled workers and for non-Germans, identity is an order of magnitude more important than geography in explaining cross-border mobility for all groups. The results continue to hold if we exclude job-to-job transitions separated by a spell of unemployment.

4   A Multi-Region Model of a Frictional Labor Market

We next develop a model to interpret our empirical findings. The model is useful because the empirical analysis has three shortcomings: first, the magnitudes we find for wage gains and worker flows are not directly interpretable because movers are selected. In particular, a model is needed to disentangle what part of workers' wage gains is due to home bias and what part is due to a worker being lucky in getting a good job offer. Second, the model is necessary for proper inference, and specifically to map the observed differences between East- and West-born workers into workers' preference for their home region, skills, and opportunities to move, and to distinguish these from generic migration costs. Finally, the model provides a laboratory to study the macro implications of the various frictions, taking into account firms' endogenous response to changes in the labor supply.

To address these issues, we develop a parsimonious model of frictional labor reallocation, which we will estimate using matched employer-employee data to determine the size of the various wedges. Our model builds 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)). Including within-region labor reallocation across firms is necessary since every move between regions is also a move between firms. We thus need to benchmark the wage gains of an across-regions move to those of a within region move across firms. Spatial frictions are generated both by mobility costs and by workers' home bias, which we will estimate. We determine regional price differences through a stylized goods market with a fixed factor of production, which will allow us to take into account congestion effects in our counterfactuals in Section 5 below. To our knowledge, we develop the first general equilibrium model that encompasses both spatial and reallocation frictions within a unified framework. While Hoffmann and Shi (2016) consider a random search environment with two sectors, they need to restrict worker flows to be in only one direction to obtain analytical solutions. Our model features worker flows in both directions, and we therefore do not obtain fully analytical solutions.

4.1   Model Setup

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

Environment.   Let time be continuous. There are $\mathbb{J} = \{1, ..., J\}$ regions in an economy which is inhabited by a continuum of mass 1 of workers of types $i \in \mathbb{I}$, with $\mathbb{I} = \{1, .., I\}$. Throughout the text, we will use superscripts for worker types and subscripts for regions. Let the mass of workers of type i be $\bar{D}^i$, where $\sum_{i \in \mathbb{I}} \bar{D}^i = 1$. Workers of type i have a preference parameter τ_j^i for being in region j, and consume both a tradeable and a local good, such as housing. Their utility is $\mathcal{U}_j^i = \tau_j^i c^\eta h^{1-\eta}$, where c and h are the amounts of tradeable good and local good, respectively. Workers also differ in their ability. Specifically, a worker of type i produces θ_j^i units of output per time unit in region j. Hence if this worker is employed at wage rate w per efficiency unit, he earns an income of $w\theta_j^i$. Worker i's indirect utility from receiving wage rate w in region j is then $\mathcal{V}_j^i = w\theta_j^i \tau_j^i / P_j$, where $P_j = (P_c)^\eta (P_{h,j})^{1-\eta}$ is the regional price level, P_c is the price of the tradeable good, and $P_{h,j}$ the price level of the local good in region j.[21] We normalize $P_c = 1$.

Workers operate in a frictional labor market. A mass e_j^i of workers of type i in region j is employed and a mass u_j^i is unemployed. An employed worker of type i located in region j faces an arrival rate of job offers from region x of $\varphi_{jx}^i \lambda_x$, where λ_x is the endogenous rate of offers from firms in region x, determined below, and φ_{jx}^i is an offer arrival wedge. This wedge captures for example that offers from

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

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

On the firm side, there is a continuum of firms exogenously assigned to regions $j \in \mathbb{J}$, where M_j is the mass of firms in region j and $\sum_{j\in\mathbb{J}} M_j = 1$. Within each region, firms are distributed over labor productivity p according to density function $\frac{\gamma_j(p)}{M_j}$ with support in a region-specific closed set $[\underline{p}_j, \bar{p}_j] \subseteq \mathbb{R}^+$.[22] Firms post vacancies to hire workers to produce output. We denote by l_j^i the measure of workers of type i employed per vacancy, and thus $\sum_{i\in\mathbb{I}} \theta_j^i l_j^i$ is the measure of efficiency units of labor used by one vacancy of the firm. Vacancies can produce any combination of the two goods according to the production functions $c = pn_c$ and $h = (pn_h)^{1-\alpha}k^\alpha$, respectively, where $0 < \alpha(1-\eta) < 1$, and n_c and n_h are the efficiency units of labor per vacancy used in the production of the two goods, which satisfy $n_c + n_h = \sum_{i\in\mathbb{I}} \theta_j^i l_j^i$. The term k is a factor that is in fixed supply, such as land, with aggregate supply in region j of K_j and equilibrium price ρ_j. Each firm p in region j decides how many vacancies $v_j(p)$ to post, subject to a vacancy cost $\xi_j(v)$, what wage rate $w_j(p)$ to offer, and how to allocate labor across the production of the two goods, taking prices in the output market as given. Each vacancy meets workers at a rate that we normalize, without loss of generality, to one. All agents discount future income at rate r.

In our model, firms compete for all worker types in one unified labor market. To our knowledge, this is a novel feature of our wage-posting environment. Previous work with heterogeneous types, see for example Moser and Engbom (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.

We next solve for the equilibrium in the goods market. We show that once the demand for land has been maximized out, the firm's wage posting problem boils down to linear maximization problem that is similar to the standard setup in the wage posting literature (e.g., Mortensen (2005)). We next turn to the labor market, which is our main focus. We discuss in more detail the problems of workers and firms, and solve for the labor market equilibrium, taking local prices as given.

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

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

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

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

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

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

Using the labor demand of the firm $n_h = \frac{\rho_j}{p} \frac{1-\alpha}{\alpha} k$ and the equilibrium price, we can simplify the firm's profits $\hat{\pi}(w)$ to obtain

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

where capital and the individual labor demands have been maximized out. The firm's profits thus boil down to a linear expression in the total number of workers, as in the standard Burdett-Mortensen framework. We will solve for the equilibrium in the labor market starting from this equation, taking the regional price index P_j as given. We first discuss the problem or workers and then the problem of firms.

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

An employed worker of type i in region j earning wage w randomly receives offers from region x with associated wage w'. Given an offer, the worker maximizes utility by solving

$$\max \left\{ W_j^i(w) + \varepsilon_d; (1 - \kappa_{jx}) W_x^i(w') + \varepsilon_a \right\},$$

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

accepts an offer is given by

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

and the expected value of an offer is

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

Similarly, an unemployed worker of type i in region j obtains random offers and compares them to the value of unemployment U_j^i by solving

$$\max\left\{U_j^i + \varepsilon_u; (1-\kappa_{jx})\,W_x^i\left(w'\right) + \varepsilon_e\right\},$$

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

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

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

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

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

The expected value of unemployment U_j^i is similarly

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

Firms. Since the firms' production functions are linear, the firm-level problem of posting vacancies and choosing wages can be solved separately. Following the literature (e.g., Burdett and Mortensen (1998)), we focus on steady state. Employers choose the wage rate that maximizes their steady state

profits for each vacancy, which are

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

where we have used that the profits from the goods market at a given wage are $\hat{\pi}(w) = p \sum_{i \in \mathbb{I}} \theta_j^i l_j^i(w)$. A higher wage rate allows firms to hire and retain more workers. On the other hand, by offering a higher wage, firms cut down their profit margin, $p - w$. The complementarity between firm size and productivity implies that more productive firms offer a higher wage, just as in the standard Burdett-Mortensen setup. However, unique to our framework, firms need to take into account that their wage posting decision also impacts the types of workers they attract and their region of origin. For example, posting a higher wage can allow a firm to also attract workers with a lower preference for being in the firm's region. Note also that since firms maximize nominal profits, they obtain an advantage from being located in a region with a lower local price level because they can provide a higher utility at a given w to workers, who consider real wages.

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

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

where $\pi_j(p)$ are the maximized profits per vacancy from (9). The size of a firm p in region j is therefore given by $l_j(w_j(p))v_j(p)$, where $w_j(p)$ is the profit-maximizing wage. Moreover, the vacancy posting policy from the firm problem gives us the endogenous arrival rate of offers from each region

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

and the wage policy gives us the endogenous distribution of offers

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

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

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

then solve for the mass of unemployed and employed workers.

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

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

where $\mathcal{P}_j^i(w) \varphi_j^i \bar{D}^i$ is the hiring rate at which a vacancy in region j gets filled by workers of type i from any region, and $q_j^i(w)$ is the separation rate. The hiring rate is given by the product of three terms. First, a firm is more likely to hire a worker of type i if the exogenous total mass of workers of this type, $\bar{D}^i$, is large. Second, hiring is more likely if workers of type i frequently receive offers (φ_j^i high). Finally, a firm is more likely to hire a worker of type i if such workers have a high acceptance probability $\mathcal{P}_j^i(w) \in [0, 1]$. This probability is in turn given by

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

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

The separation rate is given by

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

which consists of the exogenous separation rate into unemployment plus the rate at which workers receive and accept offers from other firms. In steady state, the mass of workers per vacancy is then

$$l_j^i(w) = \frac{\mathcal{P}_j^i(w) \varphi_j^i \bar{D}^i}{q_j^i(w)}. \tag{14}$$

We next turn to the mass of employed and unemployed workers, respectively. The mass of employed workers i in location j at firms paying at most w satisfies

$$E_j^i(w) = \int_{\underline{p}_j}^{\hat{p}_j(w)} l_j^i(w_j(z)) v_j(z) \gamma_j(z) \, dz, \tag{15}$$

where $l_j^i(w)$ is given by (14).

The mass of unemployed workers is defined via the flow equation

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

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

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

In steady state, the mass of unemployed workers is then

$$u_j^i \equiv \frac{\delta_j^i}{\vartheta_j^i + \delta_j^i} \bar{D}_j^i. \tag{16}$$

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

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

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

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

3. *the arrival rates of offers and wage offer distributions are consistent with vacancy posting and wage policies, according to equations (10) and (11);*

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

4.2 Characterization of the Equilibrium

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

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

$$
\begin{aligned}
w_j(p) &= w_j\left(\underline{p}_j\right) + \int_{\underline{p}_j}^{p} \frac{\partial w_j(z)}{\partial z}\gamma_j(z)\,dz \\
s_j^i(p) &= s_j^i(\bar{p}_j) + \int_{p}^{\bar{p}_j} \frac{\partial s_j^i(z)}{\partial z}\gamma_j(z)\,dz,
\end{aligned}
$$

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

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

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

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

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

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

and

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

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

Proof. See Appendix C.2. □

In order to understand the structure of our model, it is useful to compare it to the benchmark Burdett-Mortensen model. Our model collapses to the Burdett-Mortensen model when worker heterogeneity and mobility frictions across regions are shut down.[23] In this benchmark case – as is well known – the equilibrium wage policy is as follows: the lowest productivity firm sets the minimum wage that allows it to hire workers from unemployment – i.e. $w\left(\underline{p}\right) = b$ –, and the wage policy is an increasing and continuous function of productivity. As a result, workers separate either exogenously or upon receiving

---

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

a job offer from any firm with a higher productivity, $s(p) = \delta + \lambda[1 - F(w(p))]$. The wage policy must be continuous, since a discrete jump in wage cannot lead to a discrete jump in firm size, the reason being that firm size is purely determined by the ranking of wage offers and not by their level. Equilibrium wage dispersion is given by the fact that firms that pay a higher wage are able to attract and retain more workers, and thus firm size is an increasing function of wage paid.

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

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

Sources of Frictions. The model encompasses three types of frictions that prevent the allocation of workers to the most productive firms. We will estimate the size of these frictions in Section 5, and analyze how they contribute to the spatial wage gap between East and West Germany.

First, *reallocation frictions*, as in the class of models along the lines of Burdett and Mortensen (1998), prevent the reallocation of workers to more productive firms even within a region. The friction arises because firms have to pay the convex vacancy posting cost $c_j(v)$ to hire a worker, which implies

that the rate at which workers receive job offers, λ_j, is finite. Workers therefore have to wait to receive a better job offer or to exit unemployment.[24]

Second, *migration costs* hinder the mobility of labor between regions. As in spatial models with frictional labor mobility (e.g., Bryan and Morten (2017), Caliendo, Dvorkin, and Parro (2019)), workers have to pay a cost equal to a fraction κ_{jx} of their future value to move across regions. This cost may prevent workers from accepting better job offers if they involve a cross-region move.

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

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

5   Quantitative Analysis

We now estimate the model in the context of the German labor market. First, we briefly discuss the overall estimation strategy. We then provide a heuristic structural identification argument to show how the structure of the model together with appropriate empirical moments allows us to separately identify the different sources of frictions. Next, we estimate the model. Finally, we discuss the model fit and the estimated primitive parameters, and use the estimated model to structurally decompose the persistent divide between East and West Germany. We conclude this section by providing some external validation of the model.

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

5.1 Overall Estimation Strategy

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

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

Units and Functional Form Assumptions. We consider two regions, East and West Germany, and two worker types, East and West Germans. We let a unit interval of time to be one month.[25] Firms' log productivity is drawn from a Gamma distribution with scale and shape parameters $\gamma_{1,j}$ and $\gamma_{2,j}$. We assume that the scale and shape parameters are the same in both regions, and that there is a relative productivity parameter $Z > 0$ which shifts the CDF of West – i.e. for all $\log p$, $\Gamma_W (\log p + Z) = \Gamma_E (\log p)$. Consistent with this fact, we show in Figure 18 in Appendix D that the wage distribution in the West has the same shape as in the East, but is shifted to the right, while the firm size distribution is exactly the same in both regions.

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

5.2 Inference Through the Lens of the Model

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

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

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

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

---

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

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

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

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

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

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

and the relative comparative advantage from

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

To recover the four θ_j^i we need two normalizations: first, without loss of generality we pick $\theta_E^E = 1$. Second, we can only recover relative comparative advantage, since we cannot distinguish empirically between East-born workers having a disadvantage in the West and West-born workers having an advantage in the East (see Appendix B.3). We therefore impose the taste bias to be symmetric, that is we assume that $\frac{\theta_W^E}{\theta_E^E} = \frac{\theta_E^W}{\theta_W^W} \equiv \theta_h$, which attributes the relative comparative advantage equally to a disadvantage of East-born workers and an advantage of West-born workers.

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

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

28

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

Both the taste wedge τ_j^i and the mobility cost κ_{jx} affect the wage gain through their impact on the probability of acceptance $\mu_{jx}^i(w, w')$.[26] Consider the limit case when $\sigma \to 0$ – i.e. there are no preference shocks. Then, $\mu_{jx}^i(w, w') = 1$ if and only if

$$(1 - \kappa_{jx})W_x^i(w') \geq W_j^i(w). \tag{19}$$

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

The reasoning shows that the wage gains convey useful information on both the moving cost and the taste bias. To identify them separately, we need to impose the identifying assumption that the migration cost is symmetric between regions: $\kappa_{jx} = \kappa_{xj}$.[27] Furthermore, without loss of generality, we normalize $\tau_E^E = 1$. Finally, to limit the number of parameters to be estimated, we restrict the taste bias to be identical for East- and West-born workers, i.e., both East- and West-born workers are assumed to have the same disutility of living away from home. We therefore need to pin down two taste bias parameters: the taste bias for being in the home region τ_h, and the relative taste for working in the West τ_W, which simply captures the overall amenity differences across regions.[28] Equation (18) shows that the wage gains depend additionally on the endogenous wage offer and labor distributions, F_x and G_j^i. We need the structural model to control for these endogenous objects to correctly estimate the κ_{jx} and τ_j^i. Nonetheless, we can provide some intuition for the size of these parameters by comparing the relative wage gains across different types of moves.

Consider an East-born worker moving from East to West Germany. Figure (3a) shows that such moves entail on average a very large wage increase. This could be due to three possibilities: i) East German workers dislike working in the West; ii) there is a large migration cost between East and West Germany, thus leading East-born workers to accept only the very best offers; or iii) offers received from the West are on average much higher than the equilibrium wages in the East. Comparing the wage

---

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

[27]With our data, it is not possible to distinguish between a lower amenity value in the West or a higher moving cost from East to West than from West to East. We argue that if we interpret the cost κ as a literal moving cost, then it is reasonable to assume that it is symmetric. We will then charge all region and birth-place specific differences to the taste parameters τ.

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

gains of an East German worker moving from East to West to the wage gains of moving from West to East allows us to argue that migration costs cannot be the only explanation. Under our identifying assumption, movers towards the East also face a migration cost, yet their wage does not increase upon a move, as shown in Figure (3b). Similarly, comparing the wage gains of East- and West-born workers for the same move from East to West Germany allows us to argue that differences in the offer distribution cannot be the only explanation: by assumption, East- and West-born workers draw from the same distribution of offers, yet West-born workers have a much smaller relative wage increase when moving towards the West. This argument demonstrates that individuals must have a taste bias towards their home region since otherwise we should not observe the steep asymmetry between East- and West-born workers.

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

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

The separation rate is therefore the product of i) the rate at which offers from region x arrive to workers i and ii) the probability, on average, that an offer is accepted. As just discussed, the second term is pinned down by moments reflecting workers' wage gains. The first term depends on the exogenous wedges of interest, φ_{jx}^i, and the endogenous overall arrival rate of offers from region x, λ_x, which depends endogenously on the number of vacancies posted. Since, by assumption, West- and East-born workers draw offers from the same distribution, we can recover the size of the wedges from the rates of job-to-job mobility across regions and by worker types. For example, consider the separation rates of workers currently in East Germany towards the West. As we show below, West-born workers in the East move towards jobs in the West at roughly three times the rate of East-born workers. Since West- and East-born workers face the same λ_W, the difference could arise either because West-born workers receive more offers from the West ($\varphi_{EW}^W > \varphi_{EW}^E$) or because West-born workers are more likely to accept offers from the West, possibly because they have a taste or skill bias towards it. Since the taste and skill bias are already pinned down by wages, targeting the observed flows allow the model to recover the offer bias.

Following the skill and taste biases, we restrict also the offer bias to be symmetric: we assume that $\varphi_{EW}^E = \varphi_{WE}^W \equiv \varphi_{hf}$, which is the wedge for offers from the home region to the foreign region. Similarly, $\varphi_{WE}^E = \varphi_{EW}^W \equiv \varphi_{fh}$, which captures the wedge from the foreign region back home. We also assume that within region there are no offer biases, and normalize these wedges, without loss of generality, to one: $\varphi_{jj}^i = 1$ for all i and j. These restrictions reduce the dimensionality of the parameter vector to be estimated, thus tightening up the identification and focusing on the key objects of interest.

5.3 Estimation

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

To compute the empirical moments, we use both the LIAB and the BHP data, drawing on their respective advantages. The matched employer-employee data from the LIAB allow us to compute the job-to-job flows and wage gains at the individual level, which are crucial to identify the components of the home bias and the migration friction. The establishment-level BHP data, on the other hand, contain a significantly larger and more representative sample of establishments than the LIAB, which provides us with a better estimate of the firm side of the job market. We summarize the 9 directly calibrated parameters and the 13 jointly estimated ones in Table 3.

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

The share of workers born in the East, $\bar{D}^E$, can easily be computed from the LIAB. Similarly, the share of firms in East Germany, M_E, can be obtained from the BHP. We normalize the mass of firms in East and West Germany to be identical in our estimation. If we calibrated the number of firms to match the empirical mass of 18% of establishments in the East, then, since workers have to pay a migration cost when they move across regions but face no mobility cost within regions, workers in the East would have a higher chance of being contacted by a vacancy that requires the payment of a mobility cost than West German workers. We find that outcome undesirable because we see the moving cost as something that captures the actual cost of relocating, which is not specific to East or West Germany. Using an equal mass of firms in each region, we will run our estimation where all the empirical targets, and the share of workers born in the West, are appropriately re-scaled. For example, we adjust the empirically observed probability of a move from West to East Germany by a factor of $\frac{.5}{.18}$ to be consistent with the model in which 50%, rather than 18% of firms are in the East, and so on.

To set the separation rate into unemployment $-\delta_j^i$ — we perform local projections according to the specification for workers' wages after a job-to-job move (2), using the worker's probability of becoming unemployed in year τ as the left-hand variable. Figures 19a and 19b in Appendix D show that the average probability of becoming unemployed does not change for a given worker once that worker is in a different region, although it temporarily drops in the year of the job switch.[29] We therefore assume that the separation rate does not vary by current location of a worker. We set the birth-specific separation rate by computing in the LIAB the monthly probability that an employed worker separates into unemployment, for both East and West Germans.

We assume that the unemployment benefit, but not its utility value, is the same irrespective of

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[29]Conditional on a rich set of controls, the separation rate does not change upon a move across regions. Of course, unconditionally, the separation rate, as well-known, increases after any job-job migration move.

Table 3: Estimated and Calibrated Parameters

		Value
	Parameters Calibrated Outside of the Model	
(1)	$\bar{D}^E$: Share of Workers born in East	32.10%
(2)	M_E: Share of Firms in East	17.90%
(3)	δ^E: Monthly Separation Rate to Unemployment (East-Born)	0.92%
(4)	δ^W: Monthly Separation Rate to Unemployment (West-Born)	0.63%
(5)	b: Unemployment Benefit	0.50
(6)	r: Interest Rate (Monthly)	0.5%
(7)	P_E: Price Level in East Germany	0.93
(8)	$\alpha(1-\eta)$: Payments to Fixed Factors as Share of GDP	5.0%
	Estimated Skill Bias	
(9)	θ_h: Comparative Advantage towards Home-Region	0
(10)	θ_W: Absolute Advantage of West-Born	12.78%
	Estimated Remaining Home Bias and Mobility Frictions	
(11)	$1-\tau_h$: Preference for Home-Region	5.2%
(12)	κ: Mobility Cost to Cross-Regions	4.66%
(13)	φ_{fh}: Offer Bias from Home Region	10.18%
(14)	φ_{hf}: Offer Bias from Foreign Region	5.87%
	Estimated Productivity and Amenity Differences	
(15)	Z: Productivity Gain of West-Firms	12.44%
(16)	$1-\tau_W$: Preference for West Germany	−12.00%
(17)	γ_1: Variance of Firm Productivity	0.028
(18)	γ_2: Skewness of Firm Productivity	2.02
	Estimated Labor Market Frictions	
(19)	$\chi_{0,W}$: Level of Vacancy Cost (West)	0.128
(20)	$\chi_{0,E}$: Level of Vacancy Cost (East)	0.086
(21)	χ_1: Curvature of Vacancy Cost	4.525
(22)	σ: Variance of Taste Shocks	0.62
(23)	ν: Relative Search Intensity of Unemployed	2.06

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

the worker's birth-region and scaled by the productivity of the last region a worker was employed: $b_j^i = bZ_j$ for all j and i. Unemployed workers in both East and West Germany receive 60% of their previous wage if they do not have children, and 67% if they have children, for the duration of their unemployment insurance benefits, which run up to 12 or 18 months (Dustmann (2003), Caliendo, Tatsiramos, and Uhlendorff (2013)). Afterwards, they receive welfare benefits, which are lower. Empirical search models often set the reservation wage below the level of benefits (e.g., Van Den Berg (1990), Van Den Berg and Ridder (1998)), based on the assumption of a non-pecuniary disutility of being unemployed. Consequently, we set the unemployment benefit to 50% of the productivity level of the lowest productivity firm in our baseline. We perform robustness checks below and show that setting higher benefits does not meaningfully alter our results.

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

Estimating the Skill Bias   The skill bias can be estimated separately before solving for all other parameters. We implement the AKM regression (17) in the LIAB, following exactly the specification in Card, Heining, and Kline (2013), which includes additional time-varying controls for time, age, and educational attainment. We fit the model to both East and West Germany. We provide more details on the specification in Appendix B.3. 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.[30] This sample includes approximately 97% of West and East workers in the LIAB.

The results show a small *negative* comparative advantage in the home region, indicating that East-born workers actually obtain a premium in the West even after controlling for firm and fixed worker characteristics ($\beta = 0.019$). One possible explanation for this finding could be selection, since the workers that move to the West could be those whose skills are particularly valuable there. Since the presence of the premium would require the remaining frictions to be larger to rationalize the lack of East-to-West mobility, we conservatively set the comparative advantage to $\theta_h = 0$.

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

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

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

where $\hat{\alpha}_i$ is the estimated worker fixed effect, and $\mathbb{I}^i_{East}$ is a dummy for whether the worker's home region is in the East. The difference in the average worker fixed effects $\hat{\eta} = \mathrm{E}\left(\hat{\alpha}_E\right) - \mathrm{E}\left(\hat{\alpha}_W\right)$ pins down θ^W_W. We present these estimated parameters in rows (9) and (10) of Table 3.[31]

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

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

where

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

and where $m_x(\phi)$ is the value of moment x in our model given parameters ϕ, $\hat{m}_x$ is the empirically observed vector of moments, and ω_x is a vector of weights. We now discuss how we compute the 28 empirical targets used in the estimation and how they identify the remaining parameters. We present the moments assigned to five groups in Table 4, where each of the groups receives equal weight in the estimation, and within each group all moments are equally weighted. Thus, this procedure gives for example the same weight to the two moments related to the wage and GDP gap as to the eight moments related to job-to-job flows.

As discussed, the size of the taste bias and the migration friction are mainly identified from the average wage gains of job-to-job switchers that move across regions. We obtain the empirical wage gains from the wage regression (2) discussed earlier, where we take the coefficients of the year of the job move, shown in row (1) of Table 11 in Appendix E. We present the values of these targeted moments in rows (1)-(4) of Table 4. The size of the offer wedge is identified from the cross-regional flows of workers between jobs. We construct these flows by computing in the LIAB the share of workers that make a job-to-job switch from East to West or from West to East, respectively, in each month, and average each of these moments across all months in 2009-2014. We obtain the moments for both East- and West-born workers (rows (9)-(12) of Table 4). To help with the estimation, we target additionally the share of West-born workers employed in the West and the share of East-born workers in the East from the LIAB to ensure that our steady state equilibrium matches these moments closely (rows 17-18).

To determine the taste bias and the migration friction, our model needs to be consistent with the distributions of wage offers $F_x(w)$ and of the joint distribution of firm wage and size $G^i_j(w)$. We rely on moments in the BHP data to match the wage-size distribution $G^i_j(w)$. As discussed, the BHP data are preferable for moments on the firm side, since they are more representative at the firm-level. However, since the BHP does not report employment by birth-place, we cannot target distributions

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

that distinguish between East- and West-born workers. We observe the regional wage-size distributions $G_j(w)$ directly in the data, and target three moments from these distributions.[32] First, we seek to match the share of employment that is working at the 10% largest firms within each region and the skewness of the distribution of (log) firm size. These two moments provide information on the overall shape of the wage-size distribution. To construct these moments, we residualize each establishment's log number of workers by removing factors affecting size that are not in our model.[33] We then compute the share of workers in the top decile and the skewness based on the residualized size distribution in each region. These moments are listed in rows 21-24 of Table 4. We additionally target the (log-log) relationship between firm average wage and size (rows 25-26), which we obtain via a regression of establishments' log average wage on log size in each region, where we include the same controls as in the residualization. As we will show in Section 5.6, empirically the relationship between firm size and wage is log linear. The six moments identify in particular the skewness and variance of the firm productivity distribution, γ_1 and γ_2, and provide information on the level and the curvature of the vacancy cost function, which are governed by $\chi_{0,j}$ and χ_1.

The distribution of wage offers $F_x(w)$ is not observed in the data. However, as well known, the distribution of wage offers and the equilibrium distribution of workers to firms are directly linked to each other in a Burdett-Mortensen setup. The relationship between the offer distribution and the wage-size distribution is modulated by the arrival rate of offers, both on the job and from unemployment, and the separation rates. We therefore target, first, the share of workers flowing between jobs per month within a given region, computed in the same way as the flows across regions (rows 13-16). Second, we target each region's unemployment rate, which we obtain from the Federal Employment Agency (rows 19-20). These moments are sufficient to pin down, through the model's structure, the distribution of wage offers. They identify in particular the level and the curvature of the vacancy cost function, which are governed by $\chi_{0,j}$ and χ_1, and the relative matching parameter from unemployment, ν: given a separation rate from employment, which we calibrate below, a higher ν implies a lower unemployment rate.

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

Finally, we determine the variance of the taste shocks $-\sigma$. When $\sigma \to 0$, there are no preference

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[32]We do not target the actual wage dispersion in the data, since in our model wage dispersion only arises because of the competition between firms. In the data dispersion also results from worker heterogeneity, which is not in our model.

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

shocks and thus within a given region workers always climb the job ladder, reallocating from lower to higher wage jobs. Instead, when $\sigma \to \infty$, a workers has always a 50% probability of accepting a job offer, since the preference shocks swamp any other consideration. As a result, the average wage gain upon a move decreases with σ. We can therefore use the size of wage gains from within-region job-to-job moves, which have not been used so far, to discipline how important the taste shocks are (rows 5-8).

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

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

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

5.4 Estimation Results and Model Fit

Columns (1) and (2) of Table (4) compare the empirical targets to the moments generated by the estimated model. The model provides a fair fit to the data, especially considering that we are using 13 parameters to target 28 moments.[34] Importantly, the model replicates the key moments driving the identification: East-born have larger wage gains moving West and a lower probability of doing so than West-born while working in the East, and the opposite holds true for moves from West to East.

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

Table 4: Estimation Targets, Model Fit, and Counterfactuals

		(1)	(2)	(3)	(4)
		Data	Model	Taste Bias	Migr. Cost
	Average Wage Gains for Movers				
(1)	Moves from East to West (West-Born)	24.8%	30.4%	44.5%	14.4%
(2)	Moves from East to West (East-Born)	44.7%	55.6%	47.1%	43.5%
(3)	Moves from West to East (West-Born)	30.2%	26.9%	14.7%	13.5%
(4)	Moves from West to East (East-Born)	0.7%	0.9%	16.9%	-11.9%
(5)	Moves Within West (West-Born)	19.6%	14.8%	14.6%	14.9%
(6)	Moves Within West (East-Born)	15.1%	14.2%	14.4%	14.1%
(7)	Moves Within East (West-Born)	10.1%	13.1%	13.6%	12.9%
(8)	Moves Within East (East-Born)	11.1%	13.2%	13.6%	13.5%
	Rates of Job-Job Mobility				
(9)	Moves from East to West (West-Born)	0.074%	0.096%	0.035%	0.236%
(10)	Moves from East to West (East-Born)	0.021%	0.009%	0.021%	0.028%
(11)	Moves from West to East (West-Born)	0.003%	0.003%	0.008%	0.010%
(12)	Moves from West to East (East-Born)	0.058%	0.041%	0.015%	0.077%
(13)	Moves Within West (West-Born)	1.291%	0.933%	0.898%	0.933%
(14)	Moves Within West (East-Born)	1.351%	0.958%	1.076%	0.917%
(15)	Moves Within East (West-Born)	1.174%	0.816%	0.868%	0.770%
(16)	Moves Within East (East-Born)	1.108%	1.075%	1.061%	1.069%
	Regional Employment Rates				
(17)	Share of West-Born working in West	97.0%	96.6%	77.2%	95.3%
(18)	Share of East-Born working in East	83.9%	81.3%	49.9%	70.6%
(19)	Unemployment Rate in West Germany	7.0%	6.8%	7.9%	6.8%
(20)	Unemployment Rate in East Germany	11.9%	10.2%	9.6%	10.0%
	Within Region Joint Distribution of Wages-Size				
(21)	Empl. Share of 10% Largest Firms (West)	58.3%	71.1%	69.2%	71.4%
(22)	Empl. Share of 10% Largest Firms (East)	54.4%	59.3%	61.4%	59.8%
(23)	Skewness of Labor Distribution (West)	0.78	0.63	0.73	0.64
(24)	Skewness of Labor Distribution (East)	0.70	0.82	0.75	0.77
(25)	Firm's Size-Wage Premium (West)	12.5%	13.3%	13.6%	13.2%
(26)	Firm's Size-Wage Premium (East)	11.5%	14.3%	14.0%	14.1%
	Regional Wage and GDP Gaps				
(27)	West-East Gap in Firm wage	16.9%	15.1%	13.6%	14.6%
(28)	West-East Gap in GDP per worker	24.6%	28.4%	17.8%	26.6%

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

Moreover, the wage gains resulting from a move across regions are, on average, significantly larger than those associated with a move within regions.

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

The fact that our model generates the key empirical patterns builds confidence in the validity of our estimated parameters. The four key parameters of interest are in rows 11 to 14 of Table 3 and they show that: i) workers value one dollar earned while in the foreign region as 94.8 cents earned in their home region; ii) a move across regions costs 4.7% of the present discounted value of future earnings, or approximately 25,000 euros[35]; and iii) workers are more likely to receive offers from the region they are currently working in than from the other one, yet the difference is not large when compared to the very large gap in the rates of job-job mobility within and across regions.

While the magnitude of the results is specific to this context, we learn from the analysis three lessons of general interest. First, we show that a large regional wage gap and wage gains from migration can be supported in equilibrium by relatively small migration frictions. Table (1) has shown that, even when controlling for observable characteristics, real wages in the West of Germany are more than 25% larger than those in the East. Figure (3a) shows that East-born workers moving West have on average a wage increase larger than 40%. A straightforward arbitrage argument would lead us to conclude that there must equally sized frictions preventing labor to move West. Our structural analysis, instead, shows that the one-time cost of moving from East to West is only about 5% of present discounted earnings, and East-born workers pay an implicit "taste-tax" equal to another 5% of their earnings. Even adding these two frictions, we are still far from the arbitrage value, and significantly below the previously estimated average inter-state migration cost in the United States of $312,000 (Kennan and Walker (2011)). Leveraging matched employer-employee data proved crucial to reach these results. The data allow us to unpack the true wage premium in the West from unobserved individual characteristics and to benchmark workers' moves across space with workers' moves across firms, thus effectively controlling for worker selection.

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[35]Back of the envelope calculation: at an average salary of 2,500 euros per month, the present discounted value of future earnings, using $r = 0.005$ (monthly) as in the our calibration, is 500,000 euros. 25,000 is 5% of 500,000 euros.

Second, we show the importance of distinguishing between different types of spatial frictions. We show that longitudinal data can be used to distinguish migration frictions from home bias, and that these two distinct sources of spatial frictions have similar magnitude in our context. In the next section, we use the estimated model to show, through a series of structural decompositions, that they have different aggregate implications. Intuitively, home bias is more relevant in determining the persistent effects of birth-place on individual earnings, while migration frictions prevent workers from climbing a country-wide ladder. Removing migration frictions therefore leads to much larger cross-regional mobility and to stronger concentration of labor into high productivity firms.

Third, we show the danger of using observed labor flows across regions to measure how integrated the labor market is and the opportunities that workers have to take jobs in different regions. In our context, we observe that workers are dramatically more likely to make a job-to-job move within than across regions, yet we show that their skills are equally valued by firms in both regions, and that they are just slightly less likely to receive offers from the region where they are not currently working. The lower rate of mobility across regions is mostly driven by the fact that workers reject most of the offers coming from the other region due to migration costs. In other words, opportunities are there for workers to move across regions, but they often choose not to take them.

5.5 The Aggregate Role of Spatial Frictions

We now use the estimated model to study the role of different sources of spatial frictions for aggregate outcomes. We also verify that each source of spatial friction affects the empirical moments as discussed.

We compute the equilibrium under two alternatives scenarios. First, we shut down the taste bias by setting $\tau_h = 1$, keeping all other parameters unchanged. Second, we shut down migration costs across regions, $\kappa = 0$. The results for the targeted moments are shown in columns (3) and (4) of Table (4). Table (5) reports aggregate non-targeted moments, both in levels – whose units are not interpretable, but are useful to compare across cells – and relative to the benchmark estimated model.

Eliminating the Taste Bias. We first focus on the wage gains in rows (1)-(4) of Table (4): without taste bias, the asymmetry in wage gains between East- and West-born workers completely disappears. Moves towards West Germany provide a higher wage increase, since workers are drawing from a better distribution of wage offers, yet the average wage increase is almost identical irrespective of the birth-region. This result confirms the identification argument described above.

Rows (17)-(18) of Table (4) show, as expected, a large shift in the share of East-born workers working in the West and West-born workers working in the East. Since workers gain the same utility from working in either region, they are less likely to return back home. At the same time, the mixing across regions is not fully complete due to the offer bias. The higher prevalence of West-born workers in the East also decreases substantially the GDP gap – row (28) of Table (4) – due to convergence in the average skill of the labor force in the two regions.

Table (5) shows that real GDP falls slightly, decreasing by 0.35%. This result is due to the fact

that labor reallocates from the more productive West towards the East. However, as shown in rows (7) and (8) of the same table, while GDP decreases, average utility of both East- and West-born workers increases, since they are no longer paying the utility cost of being in the foreign region.

Finally, we see in Table (5) that the average wage of the firms where East-born workers are employed increases while it decreases steeply for West-born workers. This outcome is due to the fact that East-born workers reallocate towards the high paying West, while West-born are now accepting more often lower paying offers from the East. Yet, focusing on this statistic would be misleading since the average flow utility actually increases more for West-born workers. The reason is that the taste bias was keeping many West-born workers in West Germany, where the overall level of amenity is lower.

Shutting down Migration Cost. First, we focus again on the wage gains. Rows (1)-(4) of Table (4) show that shutting down the migration cost shrinks the difference between wage gains across regions, which all decrease, and wage gains within region, which are mostly unaffected. Again, this result confirms our identification arguments.

Eliminating the migration cost has a much smaller impact on the distribution of labor across regions than the taste bias, as shown in rows (17)-(18). In fact, while workers are now dramatically more likely to cross the East-West border, their long-run distribution across regions is mostly affected by their regional preferences, which keep attracting workers back to their home-region, irrespective on their current location. A direct implication is that the GDP gap between regions is also mostly unaffected by the migration cost.

The aggregate GDP and wage both increase, but only by 0.58% and 0.46%, respectively, as shown in Table (5). Shutting down the migration cost increases overall mobility, allowing workers to climb a country-wide ladder. As a result, labor concentrates towards the higher productivity firms and GDP increases.

Finally, average utility is mostly unaffected for both East- and West-born. The modest increase in the allocative efficiency of labor across firms is compensated by a worse regional allocation, since now more workers are employed away from their home region, thus paying a utility cost.

Impact on the Spatial Wage Gap. We conclude this section by commenting on the wage gap between regions. Both exercises reduce the regional wage gap, but only by a small margin. The reduction is driven by the fact that spatial barriers effectively shield East-firms from competition from the West, thus allowing them to pay lower wages. Nonetheless, the relative increase in East firms' wages is minor. The reason is that while firms in West Germany are, on average, more productive, there is a lot of overlap in the productivity distribution between the two regions. Moreover, most of the wage offers, and thus of competition for labor, are within region. As a result, for every single firm, the change in competition resulting from competition with the West is small.

Table 5: Aggregate Economic Activity

|		(1)	(2)	(3)
		Benchmark Model	Taste Bias	Migr. Cost
	Levels			
(1)	Aggregate GDP	3.026	3.015	3.044
(2)	Average Log Wage	1.016	1.014	1.021
(3)	Share of Employment in the West	36.7%	28.9%	38.6%
(4)	Share of GDP in the West	31.1%	25.7%	33.3%
(5)	Average Wage of West-Born	1.10	1.06	1.10
(6)	Average Wage of East-Born	0.97	0.99	0.98
(7)	Average Flow Utility of West-Born	1.098	1.116	1.097
(8)	Average Flow Utility of East-Born	0.965	0.971	0.966
	Percentage Deviation From Benchmark			
(1)	Aggregate GDP	-	-0.36%	+0.58%
(2)	Average Log Wage	-	-0.18%	+0.46%
(3)	Share of Employment in the West	-	-7.8%	+1.9%
(4)	Share of GDP in the West	-	-5.4%	+2.1%
(5)	Average Wage of West-Born	-	-4.90%	-0.27%
(6)	Average Wage of East-Born	-	+2.09%	+0.81%
(7)	Average Flow Utility of West-Born	-	+1.79%	-0.10%
(8)	Average Flow Utility of East-Born	-	+0.52%	+0.04%

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

5.6 Model Validation

We finally explore two external validation exercises.

First we study empirically the relationship between firm size and wage. Recall that in our model a wage gap between regions can persist even in the absence of spatial frictions if there is a productivity gap between regions and reallocation frictions that make it difficult for workers to move. However, the model predicts that if spatial frictions are present, then there must be a wage gap conditional on firm size. Figures 6a-6b illustrate this point. Figure 6a shows the wage functions of firms in the East and in the West, respectively, when there are no mobility frictions or home bias. These lines are on top of each other: without spatial frictions the location of a firm does not matter, and therefore two firms posting the same wage will in equilibrium attract the same mass of workers. However, since the productivity distribution in the West is shifted to the right, the wage distribution in the West has a longer right tail, with some firms posting wages that no firm posts in the East. Workers cannot take advantage of these higher wages due to the reallocation frictions, which make it necessary to wait for a job offer from these top firms. As a result, there is a spatial wage gap. Figure 6b presents the case with spatial frictions between East and West. In this case, firms in each region are partially shielded

Figure 6: Wage-Size Ladder in the Model and in the Data
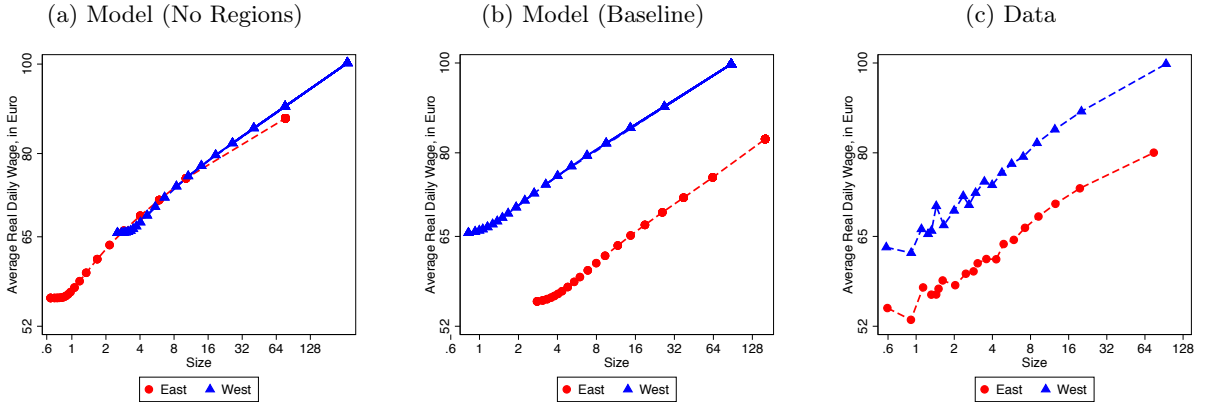
from competition by firms in the other region. Specifically, since the average productivity in the West is higher, firms in the West have to post a higher wage to attract the same number of workers. As a result, conditional on size, West firms post higher wages. We empirically confirm this sign of spatial frictions in the data. Using the residualized establishment sizes from the BHP which we obtained in Section 5.3, we classify establishments into twenty bins based on the percentiles of this size distribution, and compute the average size of establishments in each bin. We similarly obtain the distribution of residualized wages. We then plot the average residualized wage for each of the twenty size bins in Figure 6c. We find that for any establishment size, West German firms pay a higher real wage. The figure thus confirms a central implication of our model.

Second, we analyze the wage gains of workers that start commuting across regions, rather than migrate. While commuters obtain a job offer from region $j' \neq j$, we might expect them to evaluate their job offer at their current region's preference τ_j^i. Consequently, we would expect them to obtain smaller wage gains. In the data, we found from our baseline regression (2) that the wage gains of commuters for cross-region moves away from the home region are only about one third to one half as large as the wage gains from migrants (Table 11 in Appendix E). This result aligns well with the intuition provided by the model.

6   Interpretation of Workers' Home Preference

6.1   Further Results for Interpretation and Robustness

We conclude by documenting three additional facts that shed some light on the sources of workers' home preference.

We begin by examining the role of child birth on workers' mobility, and exploit the fact that the SOEP contains a variable which records whether individuals had a child. Using the Old Sample in the

Figure 7: Child Birth Event Study

(a) East to West Return Move Probability   (b) West to East Return Move Probability
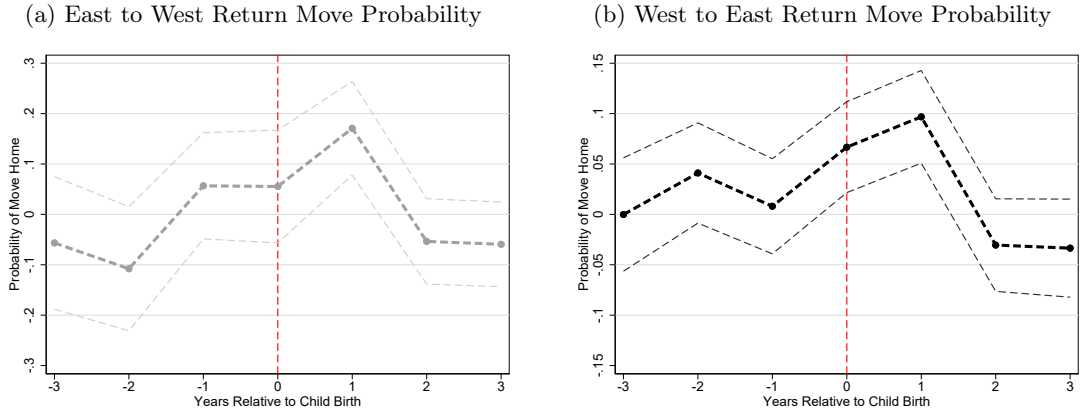
SOEP, we focus on the sub-sample of full-time workers that are employed at time t in their non-native region (which is known with certainty) and run

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

where $Migr_{it}$ is a dummy that is equal to one if worker i moves back to her home region at time t, and $\mathbb{D}_\tau$ are dummies around a child birth event (at $\tau = 0$).[36] Figure 7a shows the estimated coefficients for East-to-West return moves of West-born workers, while Figure 7b presents the coefficients for West-to-East return moves of East-born workers. We find a significant spike of 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 preempt the construction of the wall. These "East-tied" individuals were more likely to settle in counties with available houses. We can replicate the same identification strategy as in Burchardi and Hassan (2013) and use housing destruction due to WWII as an instrument for the inflow of these individuals, with migration flows as dependent variable. Columns (1) and (2) of Table 6 regress the gaps in the destination and origin fixed effects from regression (3) on the instrumented inflows of East-tied individuals.[37] Coefficients are normalized in terms of standard deviations. The results have the expected sign – counties in the West that exogenously received more East-tied individuals before 1961 are also relatively more attractive for East-born individuals in 2009-2014. The coefficients are large in magnitude; however, they are either non-significant (Column 1) or marginally significant (Column 2).

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

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

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

	(1)	(2)	(3)	(4)
	$\gamma_d^E - \gamma_d^W$	$\delta_o^E - \delta_o^W$	γ_d^E	δ_o^E
Share Expellees (Sov. Sec.) '61	.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.

Since the gap between East-born and West-born fixed effects is likely to be measured with significant noise, in Columns (3) and (4) we replicate the same analysis using simply the county fixed effects for East-born workers as dependent variable, and controlling for the fixed effects of West-born workers. The point estimates are comparable and now have stronger statistical significance. The large and positive coefficients on the West-born fixed effects indicate that East- and West-born fixed effects are highly correlated, consistent with workers from both regions assigning the same ranking to counties of a given region.

We finally consider worker flows not only across regions but also across federal states in Germany. If home bias is important, it should also affect workers' mobility across different federal states, and our findings might partially reflect attachment to a home state. To show that home bias by region plays an important role, we re-run the cross-county mobility regression with dummies (equation 4), but in addition to the three dummies for cross-border moves ($\mathbb{I}^{R(o) \neq R(d)}$), moves to the home region ($\mathbb{I}^{R(d)=h}$), and moves away from the home region ($\mathbb{I}^{R(o)=h}$), we add three additional dummies for moves across states ($\mathbb{I}^{S(o) \neq S(d)}$), moves to the home state ($\mathbb{I}^{S(d)=h}$), and moves away from the home state ($\mathbb{I}^{S(o)=h}$), where S denotes federal states and h refers to the home region or home state. We determine home states analogously to home regions. Let $\mathbb{K} = \{R(o) \neq R(d), R(o) = h, R(d) = h\}$ and $\mathbb{M} = \{S(o) \neq S(d), S(o) = b, S(d) = b\}$ capture these possibilities. We thus run:

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

44

Table 7: 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.

Column (1) of Table 7 presents the results. We find that there is a significant bias towards the home state. However, even after accounting for the home state effect, there is still a 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 or region bias.

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

7   Conclusion

In this paper, we use matched employer-employee data to carefully measure the frictions contributing to the lack of worker mobility across space. Our approach yields three novel insights: first, we show

that a large regional wage gap and wage gains from migration can be supported in equilibrium by relatively small migration frictions, given cross-regional differences in firm productivity and a frictional labor market. These frictions are an order of magnitude smaller than previously estimated. Second, we argue that it is important to distinguish between different types of spatial frictions, such as home bias and mobility costs, since their removal has different aggregate effects. Finally, we argue that it cannot be concluded from a lack of flows across regions that the labor market is not integrated. In the example of Germany, workers remain many job offers from the other region, yet they choose not to accept them.

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

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Appendix

A   Historical Overview

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

The German reunification completely removed the East German institutions of the planned economy and replaced them with West German ones. Starting on July 1, 1990, the two Germanys started a full monetary, economic, and social union, and introduced the regulations and institutions of a market economy to the GDR. These included for example the West German commercial code and federal taxation rules, as well as a reform of the labor market which imposed Western-style institutions (Leiby (1999)). At the same time, the West German Deutschmark (DM) became the legal currency of both halves of Germany. Wages and salaries were converted from Ostmark into DM at a rate of one-to-one, as were savings up to 400DM. While the currency reform implied an East German wage level of about 1/3 the West German level, in line with productivity, the switch meant that East German firms lost export markets in Eastern Europe, since customers there could not pay in Western currency. Additionally, East German customers switched to Western products, which were of much higher quality than East German ones (Smolny (2009)). West German unions negotiated sharp wage increases in many East German industries, which were not in line with productivity gains but driven by a desire to harmonize living conditions across the country (Burda and Hunt (2001), Smolny (2009)). As a consequence, East German unit labor costs rose sharply, and output and employment collapsed (Burda and Hunt (2001)). This trend was further exacerbated by the break-up and transfer of unproductive East German conglomerates to private owners, who usually downsized or closed plants.[38]

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[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   Empirical Exercises

B.1   Growth Accounting

West German GDP per capita in real terms (adjusted for cost of living differences as in the main text) is still around 40% larger than in the East (Figure 8). We perform a standard accounting exercise to decompose this GDP gap into its different components. We follow the literature and assume an aggregate Cobb-Douglas production function, with elasticities to labor and capital equal to $1 - \alpha$ and α, respectively. We set, as usual, α equal to $\frac{2}{3}$. 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 separately 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
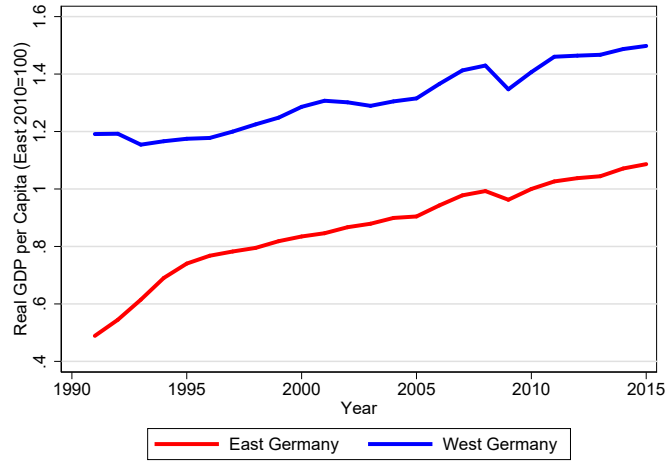
$$
\underbrace{\log y_{W,t} - \log y_{E,t}}_{\text{GDP p.c. gap}} = \underbrace{\log A_{W,t} - \log A_{E,t}}_{\text{TFP gap}} + \underbrace{\alpha \left(\log k_{W,t} - \log k_{E,t}\right)}_{\text{Capital p.c. gap}} + \underbrace{(1 - \alpha) \left(\log l_{W,t} - \log l_{E,t}\right)}_{\text{Workers p.c. gap}}.
$$

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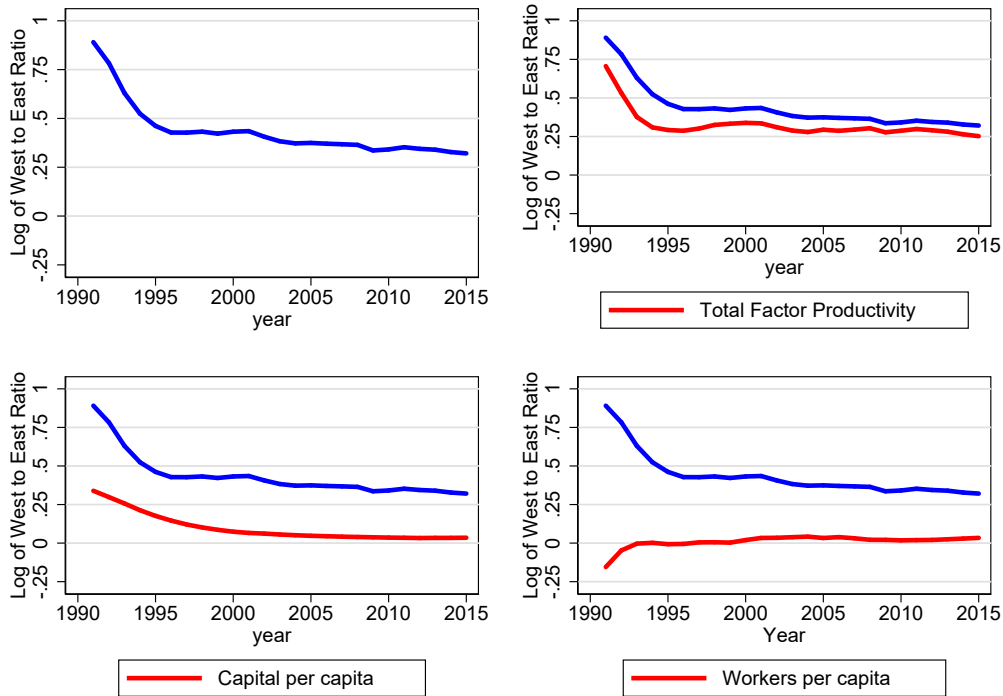
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[39]We compute all statistics excluding Berlin to be consistent with the main text.

Figure 8: Real GDP per Capita

Figure 9: Decomposition of the Real GDP per Capita Gap

B.2 Taxes

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

First, the income tax and the value-added tax are the same anywhere in Germany.[40] Similarly, the corporate tax rate is the same.[41]

Second, all companies are subject to a business tax that is levied at the level of the individual community. The tax consists of the product of i) the business income, ii) a base rate, and iii) a leverage ratio. The business income is computed in the same way across Germany, and the base rate is 3.5% everywhere. The leverage ratio varies across communities. Figure 11a shows these leverage ratios, and highlights that there are no systematic differences between East and West.

Third, the government collects taxes on behalf of the church. This church tax is higher in the South than in the North of Germany, but does not vary between East and West (Figure 11b).

Finally, property taxes are relatively low in Germany, accounting for about 0.44% of GDP in 2010, significantly lower than in most of the EU (Paetzold and Tiefenbacher (2018)). There are two types of property tax, Property Tax A (for agricultural properties) and Property Tax B (for everything else). The latter accounts for the vast majority of tax receipts from this income source. The property tax is calculated as the product of i) the property's "rateable value", ii) a base rate, and iii) a leverage ratio.[42] The rateable value is determined by a federal law on valuations. For West Germany, it is determined by a land census in 1964, while, due to the division of Germany, the rateable value for property in East Germany is mostly still based on the census from 1935. The base rate depends on the type of building, with different rates for example for residential property and agricultural property. It also differs across East and West Germany, with East Germany having on average higher base rates for similar types of properties. Finally, the leverage ratio is determined at the level of the individual community. We present the leverage ratios for the two types of property tax in Figures 12a and 12b, displayed in percent (e.g., 180 means a collection rate of 180%). While there are significant differences in ratios across communities, the ratios are not systematically different in East Germany than in the West.

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

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

[42]See Bird and Slack (2002).

Figure 10: Business Tax and Church Tax

Business Tax

Church Tax
2010

| 900 |
| 456 |
| 328 |
| 200 |
| No Data |

| 9 |
| 8 |
| Berlin |

(a) Business Tax

(b) Church Tax
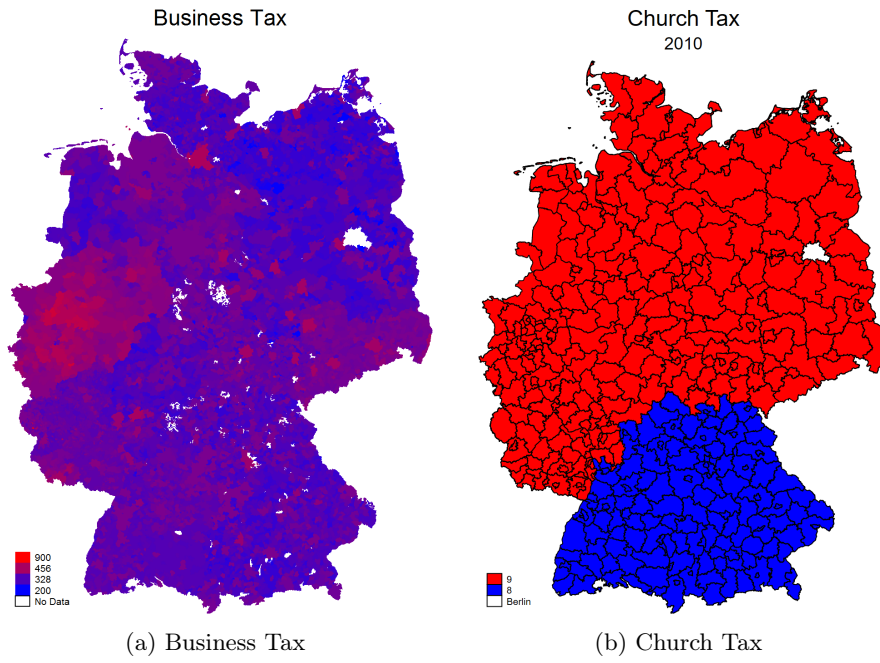
Figure 11: Leverage Ratios for Property Taxes

Property Tax A

Property Tax B

| 1800 |
| 557 |
| 278 |
| 0 |
| No Data |

| 900 |
| 576 |
| 288 |
| 0 |
| No Data |

(a) Property Tax A

(b) Property Tax B
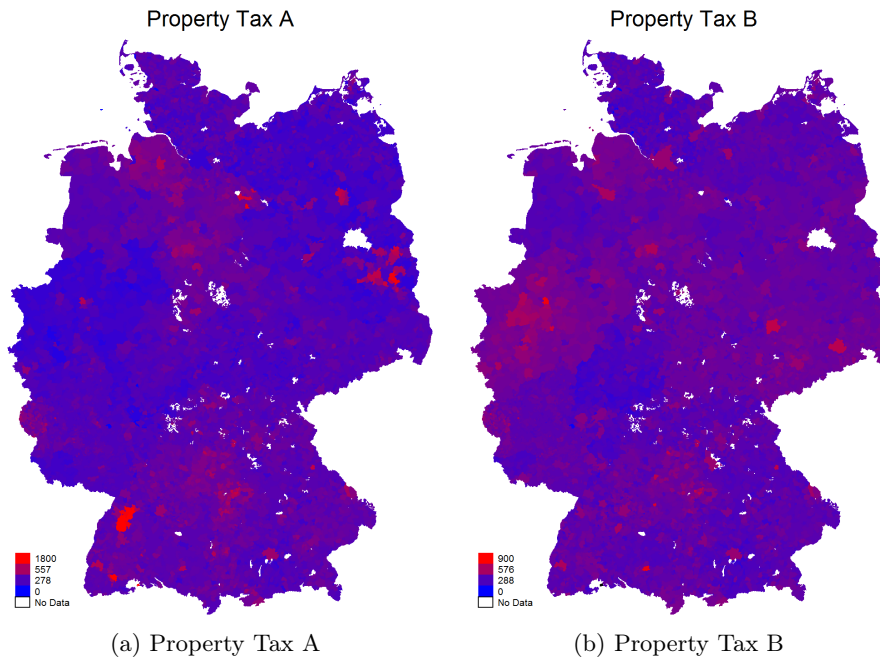
B.3 AKM Decomposition

Specification of the Baseline Model

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

$$w_{it} = \alpha_i + \psi_{J(i,t)} + BX_{it} + \epsilon_{it}, \tag{24}$$

where i indexes full-time workers, t indexes time, and $J(i,t)$ indexes worker i's establishment at time t.[43] 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.[44]

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 12a 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 12b-12d then show how these data identify the three AKM components. First, as depicted in Figure 12b, the individual components are identified from comparing the wages of 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 12c 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 12d 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
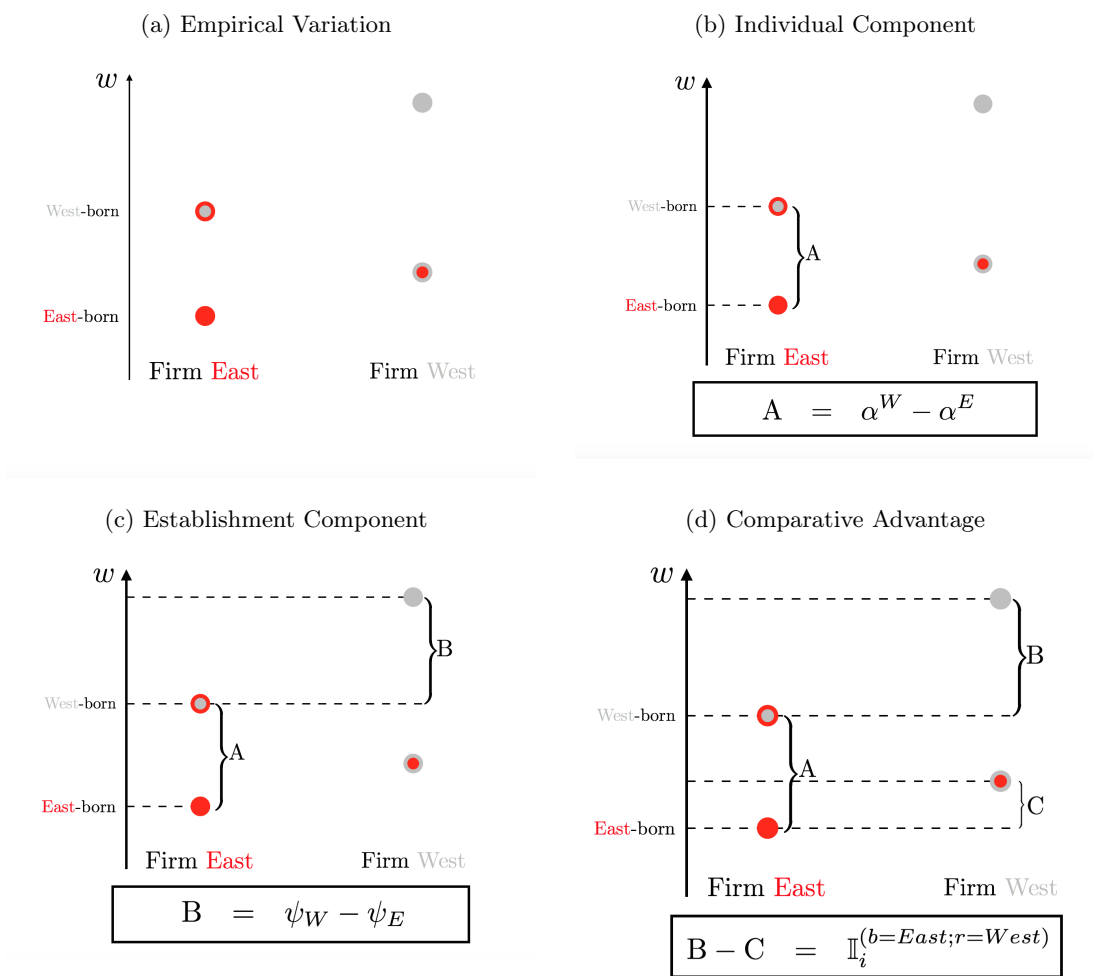
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[43]Time is a continous variable, since, if a worker changes multiple firm within the same year, we would have more than one wage observation within the same year.

[44]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.

the comparative advantage.

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 12: Identification of the AKM Components

(a) Empirical Variation

w

West-born

East-born

Firm East   Firm West

(b) Individual Component

w

West-born

East-born

Firm East   Firm West

$$\text{A} \quad = \quad \alpha^W - \alpha^E$$

(c) Establishment Component

w

B

West-born

A

East-born

Firm East   Firm West

$$\text{B} \quad = \quad \psi_W - \psi_E$$

(d) Comparative Advantage

w

B

West-born

A

East-born   C

Firm East   Firm West

$$\text{B} - \text{C} \quad = \quad \mathbb{I}_i^{(b=East;r=West)}$$

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.

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C Proofs

C.1 Equilibrium in the Goods Market

The firm's problem is

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

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

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

and assuming that both goods are supplied in equilibrium

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

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

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

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

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

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

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

Combining demand and supply yields

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

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

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

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

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Combining this expression with the demand equation (28) gives

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

as desired.

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

C.2   Proof of Proposition 1

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

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

and, as shown,

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

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

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

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

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

From equation (31), we find

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

We then define the functions in terms of p,

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

so that

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

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

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

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

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

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

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

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

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

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

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

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

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

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$F_j(w),$

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

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

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

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

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

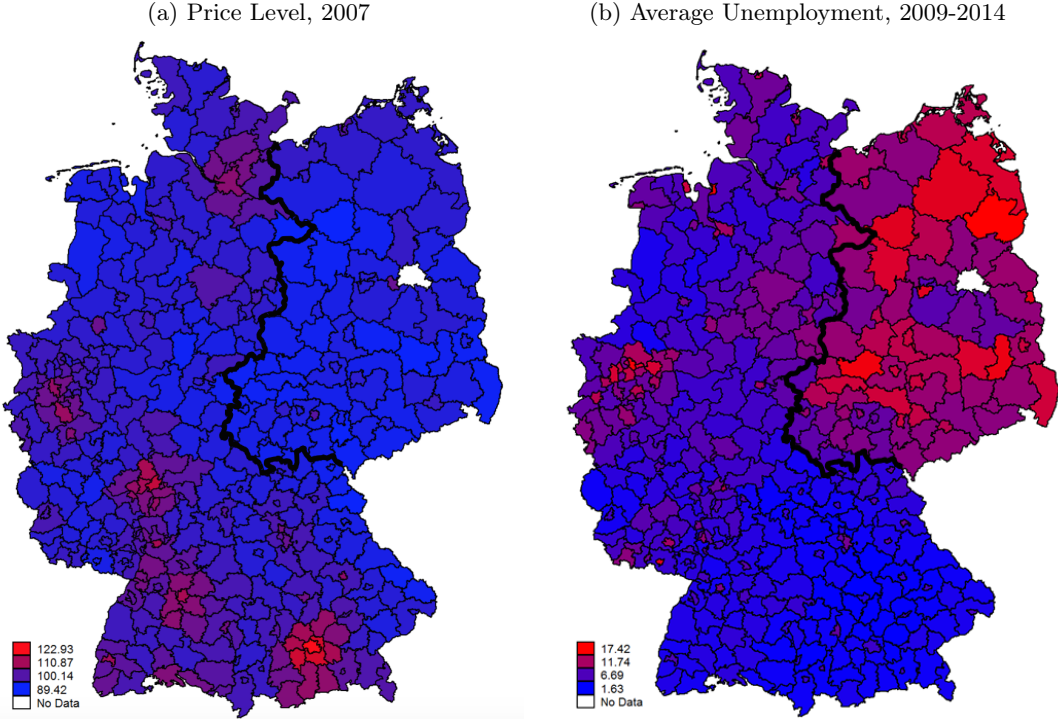We have thus proved that the wage is given by

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

and the separation rate function is

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

D Additional Figures

Figure 13: Price Level and Unemployment

(a) Price Level, 2007

(b) Average Unemployment, 2009-2014

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

Figure 14: Cumulative Distribution Functions of Real Wages in East and West
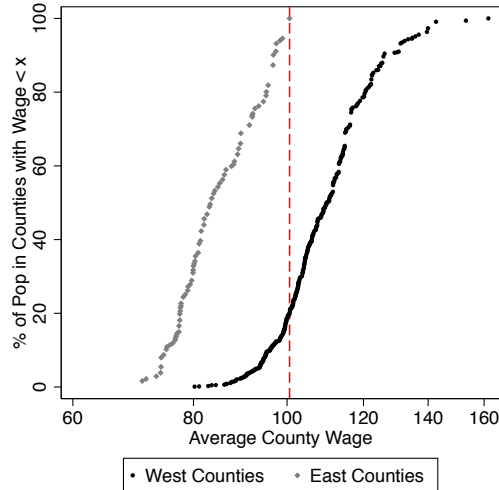
Note: The figure shows the CDF of real wages across East and West German counties. Each dot is a county, where the steepness of the CDF is determined by the share of each region's population captured by the county. The red-dashed line shows the average real wage of the highest-paying county in East Germany. Source: BHP.
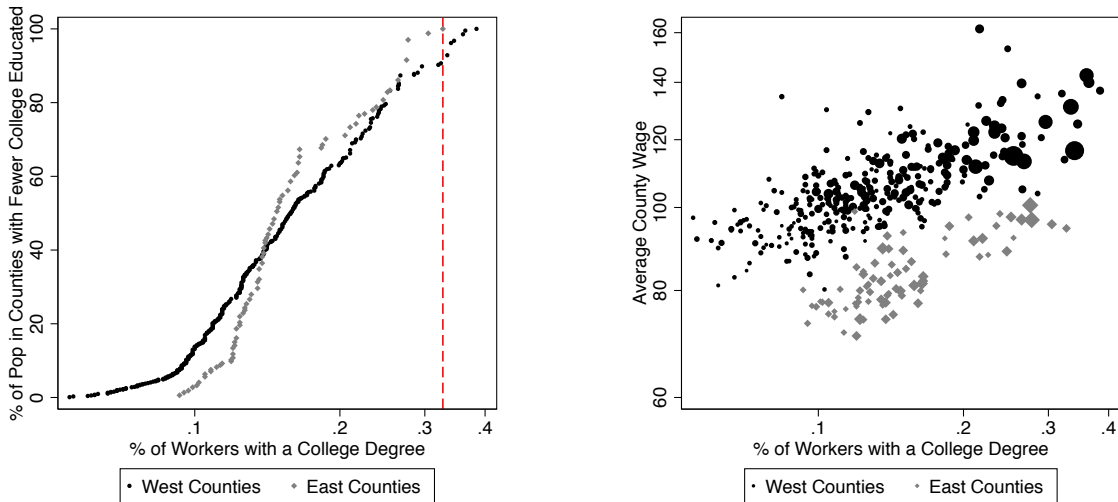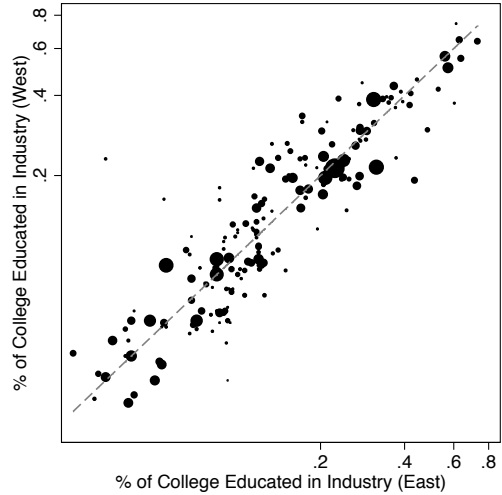

(a) CDF of the Share of Highly-Skilled Workers by County (b) Real Wage by Highly-Skilled Share Across Counties

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.
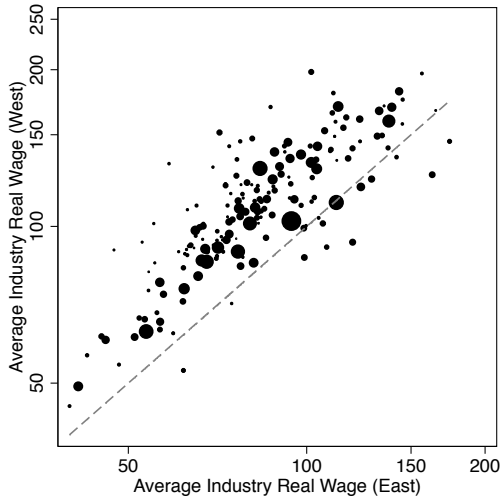
(c) Real Wage Gap by Industry   (d) Share of College-Educated by Industry in East vs. West

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.
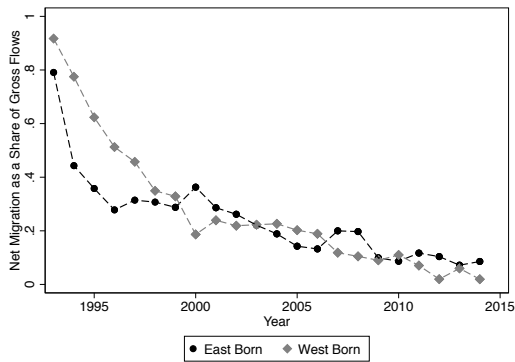
Figure 15: Real Wage by Share of Males Across Counties
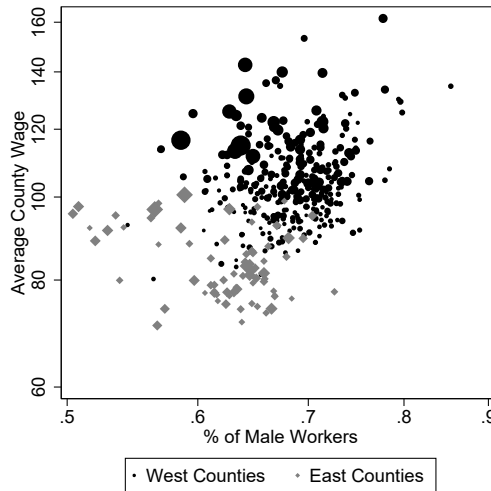
Notes: The figure plots the share of full-time male workers in each county against the average real wage of the county. The size of each dot is determined by the population in each county. Source: BHP.

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Figure 16: East-West Mobility over Time

(a) Net Flows Across Regions by Home Region

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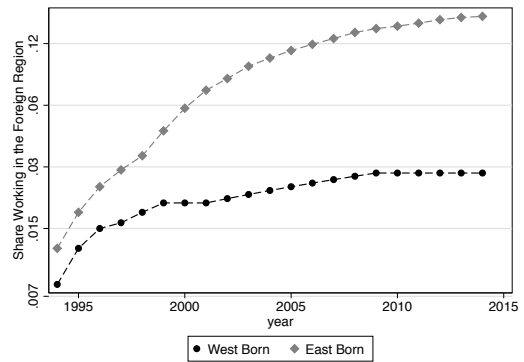
Notes: The left figure shows the number of workers moving out of their home region minus the number of workers moving back in a given year, divided by the total number of workers moving across regions. The right figure plots the share of workers by home region currently working in the other region. Each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

Figure 17: Origin FE
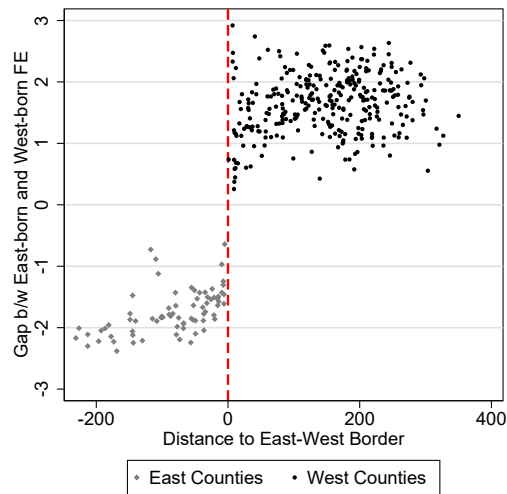
Notes: The figure plots the difference between the origin fixed effects for East- and West-born workers obtained from regression (3), plotted as a function of the county distance to the East-West border. A negative gap implies that East-born workers are less likely to move out of a given county, i.e., they have a smaller origin fixed effect than West-born workers for that county.

Figure 18: Firm Wage and Size Distributions in East and West
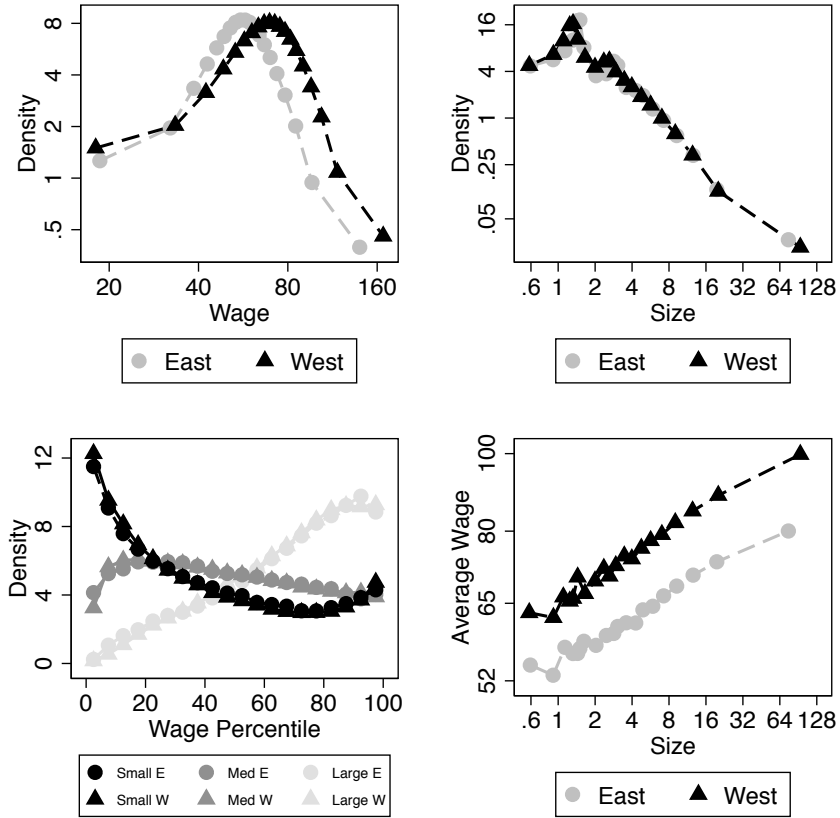
Source: BHP. Notes: The figure plots the joint distribution of firm size and wage in East and in West Germany. Both size and wage are residualized to account for variation that is not in our model, by regressing the raw log size and log wage on 3-digit industry dummies and time dummies, for East and West Germany separately. We then generate the residualized wage as the residuals from this regression plus the mean of the wage in the given region. We perform a similar exercise for size. The top left panel shows the resulting wage distributions in East and in West Germany. The top right panel presents the size distributions. The bottom left panel presents cuts of the joint distribution by plotting the density of the wage distribution at different percentiles of wages, for "small" firms (all firms up to the 15th percentile of the size distribution), "medium" firms (all firms between the 45th and 55th percentile), and "large" firms (above the 85th percentile). The bottom right panel shows the firm size plotted against the wage.

Figure 19: Probability of Unemployment for Cross-Region Moves

(a) East to West Move
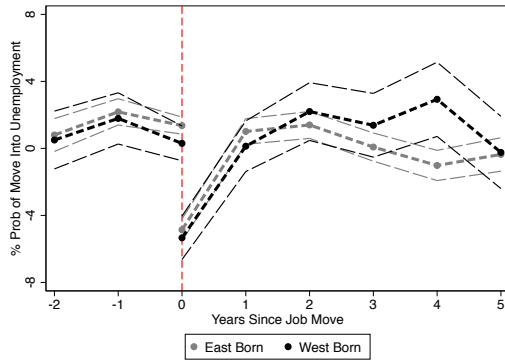
(b) West to East Move
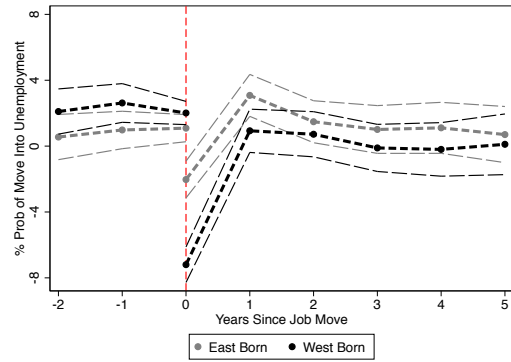
E   Additional Tables

Table 8: Effect of Region on Real Wage

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

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

Table 9: Imputed Home Region in the LIAB vs. Birth Region in the SOEP

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

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

Table 10: Wage Gaps by Home Region in the LIAB and Birth Region in the SOEP

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

Notes: ∗, ∗∗, and ∗∗∗ indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the individual level. $\mathbb{I}_i^{East}$ is the imputed home region dummy using the same procedure as in the LIAB. $\mathbb{I}_i^{East,b}$ is a dummy for a worker's birth region or schooling region.

Table 11: Wage Gains Robustness

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

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

Table 12: 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
Age controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	4,366,963	1,745,245	1,026,916	5,095,292	2,399,693	1,573,734	2,148,781	339,387

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. Standard errors are clustered at the individual level. Workers with college are workers with a value of 5 or 6 in the B2 code. Young workers were born from 1975 onwards. Middle-aged workers were born 1965-1974. Older workers were born before 1965. Non-Germans are those workers that are recorded as having non-German nationality in the LLAB data.

Table 13: Summary Statistics on Mobility

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

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

Table 14: Gravity

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

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

Table 15: Gravity Equation for Sub-Groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline	Males	Females	College	No college	Young	Middle	Older	Non-German	No unemp
$\mathbb{I}^{East}$	.1564***	.1642***	−.0475***	.2435***	.1236***	−.0249***	.3441***	.0704***	1.0737***	.1683***
	(.0071)	(.0076)	(.0115)	(.0116)	(.0076)	(.0089)	(.0105)	(.0110)	(.0229)	(.0189)
ϕ_{50-100}	−1.8128***	−1.7278***	−1.5692***	−1.0707***	−1.8340***	−1.6926***	−1.4936***	−1.4891***	−1.2353***	−1.7224***
	(.0187)	(.0189)	(.0200)	(.0194)	(.0190)	(.0187)	(.0199)	(.0214)	(.0251)	(.0189)
$\phi_{101-150}$	−2.5488***	−2.4143***	−2.1287***	−1.4762***	−2.5640***	−2.3488***	−2.0042***	−1.9746***	−1.5205***	−2.3939***
	(.0184)	(.0187)	(.0204)	(.0198)	(.0188)	(.0187)	(.0203)	(.0217)	(.0268)	(.0188)
$\phi_{151-200}$	−2.8004***	−2.6302***	−2.2834***	−1.5808***	−2.7941***	−2.5499***	−2.1195***	−2.1090***	−1.5927***	−2.6061***
	(.0184)	(.0187)	(.0207)	(.0201)	(.0189)	(.0187)	(.0205)	(.0221)	(.0278)	(.0188)
$\phi_{201-250}$	−2.9121***	−2.7286***	−2.3417***	−1.6314***	−2.9032***	−2.6380***	−2.1516***	−2.1401***	−1.6570***	−2.6961***
	(.0185)	(.0188)	(.0210)	(.0205)	(.0190)	(.0190)	(.0205)	(.0220)	(.0297)	(.0190)
$\phi_{251-300}$	−2.9669***	−2.7754***	−2.3650***	−1.6535***	−2.9452***	−2.6725***	−2.2042***	−2.1523***	−1.6502***	−2.7442***
	(.0187)	(.0190)	(.0213)	(.0211)	(.0191)	(.0192)	(.0209)	(.0224)	(.0297)	(.0192)
$\phi_{301-350}$	−3.0074***	−2.8111***	−2.3672***	−1.6701***	−2.9846***	−2.7112***	−2.1915***	−2.1443***	−1.6812***	−2.7781***
	(.0189)	(.0193)	(.0219)	(.0219)	(.0194)	(.0194)	(.0216)	(.0232)	(.0299)	(.0195)
$\phi_{351-400}$	−3.0536***	−2.8535***	−2.4029***	−1.7064***	−3.0296***	−2.7498***	−2.2273***	−2.1956***	−1.7018***	−2.8225***
	(.0191)	(.0195)	(.0224)	(.0223)	(.0197)	(.0198)	(.0221)	(.0233)	(.0316)	(.0198)
ϕ_{401+}	−3.1369***	−2.9287***	−2.4343***	−1.7564***	−3.1008***	−2.8126***	−2.2798***	−2.1936***	−1.7359***	−2.8904***
	(.0187)	(.0191)	(.0213)	(.0211)	(.0191)	(.0192)	(.0210)	(.0225)	(.0292)	(.0192)
$\mathbb{I}(R(o){\neq}R(d))$	.0265***	.0390***	.0115	−.0397***	.0478***	.0815***	.0077	−.0130	.2314***	.0281***
	(.0081)	(.0085)	(.0118)	(.0124)	(.0085)	(.0094)	(.0111)	(.0117)	(.0240)	(.0090)
$\mathbb{I}(R(o){=}b)$	−1.6285***	−1.6354***	−1.8305***	−1.6465***	−1.6733***	−1.7593***	−1.6779***	−1.8614***	−1.6417***	−1.6696***
	(.0065)	(.0069)	(.0105)	(.0105)	(.0070)	(.0080)	(.0095)	(.0103)	(.0199)	(.0073)
$\mathbb{I}(R(d){=}b)$	0.6005***	.5579***	.4525***	.3599***	.5745***	.5785***	.4084***	.4022***	.2733***	.5526***
	(.0065)	(.0070)	(.0100)	(.0107)	(.0069)	(.0078)	(.0097)	(.0102)	(.0216)	(.0074)
Observations	94,203	81,211	42,652	33,875	84,441	69,415	40,835	38,016	16,166	75,823

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

Table 16: Migration Regressions - Benchmark, Additional Coefficients

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

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