The spatial equilibrium with migration costs[*]

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Preliminary draft - results may change

August 21, 2019

Abstract

We extend the standard spatial equilibrium framework in that we model how utility-maximizing migration decisions lead to spatial arbitrage, allowing us to solve for rather than assume a long-run spatial equilibrium. To this end, we develop a quantitative spatial model in which heterogeneous workers make location decisions facing region-group-specific labour-market-related agglomeration benefits, region-specific housing-market-related agglomeration costs, and group-specific bilateral migration costs. The model remains tractable and amenable to empirical analysis because of stochastic amenity shocks with group-specific variance. We estimate the structural parameters of the model exploiting comprehensive German labour and housing market micro data and exogenous variation that originates from trade shocks, Germany's division, and deep history. Our quantitative framework can be used to evaluate the aggregate and distributional effects of arbitrary spatial shocks to productivity, amenity, or housing supply in general equilibrium, with and without migration costs. Using trade shocks, land use regulations, and regional transfers as cases in point, we illustrate how spatial shocks lead to winning and losing workers within winning and losing regions and place-based policies affect the spatial distribution of worker welfare.

Key words: Migration, gravity, amenity, productivity, spatial equilibrium, welfare

JEL: R38, R52, R58

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A   Introduction

The spatial equilibrium going back to Ricardo (1817) is arguably the single most important concept in urban economics. Perfect mobility implies that any difference in productivity or amenity between places must be compensated for by differentials in wages and prices. From this assumption, a large body of urban economics theory summarized in Fujita et al. (2001) and Redding and Rossi-Hansberg (2017) has derived determinate predictions for the effects of exogenous factors such as transport costs, production fundamentals, or various spatial policies on endogenous variables such as densities, wages, and housing costs. For decades, the spatial equilibrium framework as developed by Rosen (1979) and Roback (1982) has spurred empirical research evaluating the determinants of productivity and amenity, often with the aim of informing policy. As Glaeser (2008) puts it, the spatial equilibrium is for urban economics what the no-arbitrage condition is for financial economics.

While standard spatial equilibrium models generally do a good job in describing the spatial distribution of economic activity and the factor prices of labour and land, the assumption of perfect mobility is at odds with some increasingly notable manifestations of spatial inequalities. As an example, the discontent about the local effects of globalization that seemingly led to political polarization in trade-exposed regions in the US (Autor et al., 2016), is inconsistent with a frictionless spatial economy. Within the established spatial equilibrium framework, workers in declining regions are free to move to take advantage of economic opportunities in thriving regions and those who choose to stay put will be compensated by affordable housing. In short, the established spatial equilibrium framework is more suitable for the evaluation of the aggregate than the distributional effects of spatial shocks and policies.

To address this limitation, we develop a new quantitative spatial model with heterogeneous workers and migration costs. In contrast to the Rosen (1979)-Roback (1982) framework, we do not assume that utility is equalized across space. Since spatial arbitrage is costly, our framework features persistent spatial differences in utility levels within groups of homogeneous workers in equilibrium. In contrast to Desmet et al. (2018), who also relax the spatial equal-utility constraint by incorporating bilateral migration costs, we do not assume that the spatial economy is in equilibrium when identifying the primitives of the model. Our central contribution is to model explicitly how utility-maximizing migration decisions lead to spatial arbitrage and to show how to use data and the structure of our model to solve for the spatial equilibrium with migration costs. Our theoretical framework is built

on the idea that shocks to exogenous regional productivity, amenity and housing supply distort the spatial equilibrium, whereas costly spatial arbitrage through endogenous migration leads to mean-reversion towards the spatial equilibrium. The spatial equilibrium with migration costs is then a counterfactual situation to which an empirically observed spatial economy would converge in the absence of further exogenous shocks.

This novel feature of our theoretical framework facilitates an important contribution to the literature on place-based policy evaluation (Kline and Moretti, 2014; Neumark and Simpson, 2015). Taking the spatial equilibrium with migration costs as a starting point, we show how to use the model to conduct equilibrium-to-equilibrium counterfactual analyses of the general equilibrium effects of spatial shocks under the *ceteris paribus* assumption in the presence of migration costs. This way, we separate the causal effects of the shock from the spatial economy's mean-reversion tendency. Because our framework incorporates migration costs, we can quantitatively account for changes in the relative distribution of utility across space, which are ruled out by assumption in any policy evaluation within the Rosen (1979)-Roback (1982) framework. Our approach is very flexible and allows for the evaluation of the aggregate and distributional effects of any spatial shock or policy that can be expressed as an exogenous change in locational productivity, amenity or housing supply. We provide illustrative evaluations of general equilibrium effects on regional employment, wages, rents, and welfare using localized effects of globalization, changes in land use regulation, and regional transfers as cases in point.

An innovative aspect of our model is that we treat migration as an investment decision in which workers trade a greater present value of expected utility from consumption at a potential destination against the sunk cost of losing social capital embedded in the origin. In many other respects, the model follows recent developments in quantitative spatial economics. It incorporates an arbitrary number of regions as well as exogenous and endogenous productivity, amenity, and land supply as well as idiosyncratic shocks to amenity that lead to imperfect spatial sorting and keep the model tractable and amenable to empirical analysis. Importantly, as the dispersion of amenity shocks decreases, there are fewer idiosyncratic reasons to migrate to specific destinations, so that migration costs become relatively more important. The interaction of migration costs and the dispersion of amenity shocks to which we refer as migration resistance determines how quickly workers respond to differences in real wages and amenity in their location decisions. The model also features inter-group and inter-region redistribution via tax-financed local public services. Importantly, inelastic supply of land generates a congestion force which

ensures that the consequence of migration is to eliminate its causes. Intuitively, migration into a productive region with high real wages and expected utility, increases housing costs through competition on housing markets, which in turn reduces migration incentives.

Our model is designed with the aim of facilitating the quantitative evaluation of distributional effects of spatial shocks in general equilibrium. Therefore, the model features an arbitrary number of worker groups differing in terms of amenity preferences, exogenous productivity, migration costs, and idiosyncratic location attachment. The group-specific resistance to migrate that originates from the combination of migration costs and idiosyncratic attachment then interacts with spatially heterogeneous shocks along several important dimensions that are beyond the standard spatial equilibrium framework. First, workers moving from losing to winning regions leave part of the welfare gain behind due to the cost of migration. Second, in losing regions, welfare decreases for staying workers to whom the cost of migration outweighs the potential gains. Third, in winning regions, stayers may be net losers as in-migration congests the housing market. Because all workers compete on the same regional housing markets, groups with a large migration resistance and low returns to agglomeration will suffer most from positive regional shocks.

To solve for the spatial equilibrium with migration costs we define sufficient conditions that characterize the spatial equilibrium. Besides labour and land market clearing, the only condition we impose is that migration is neutral in the sense that the distribution of employment across regions is stationary. We show that for plausible parameter values and given values of exogenous productivity and amenity, housing total factor productivity, and migration costs, there is an equilibrium distribution of employment that uniquely pins down the spatial equilibrium. Further, we show how to identify the critical parameter values and the unobserved exogenous variables in the model using data on observed endogenous variables. In addition to data on employment, wages, and housing costs, which are conventional inputs into spatial equilibrium models, solving for the spatial equilibrium with migration costs requires data on bilateral migration.

To this end, we leverage on a matched employer-employee data set covering the universe of German workers, who we track over space and time. In particular, we observe the workplace, the nominal wage, and a range of characteristics including age, gender, and education for all years from 1993 to 2017. Aggregation of these micro data yields total employment and bilateral migration by region, year and worker groups based on age, gender, and skills. To these data, we merge a regional mix-adjusted property price index starting in 2007, which we generate from prop-

erty micro data. Equipped with this data set, we document some stylized facts of the spatial economy that motivate the the basic structure of our model. In particular, wages and housing costs both increase in density, but the former increase at a slower rate across all skill groups. Workers tend to migrate into regions where nominal wages are high and, where there is sizable in-migration, housing costs tend to increase. The propensity to migrate declines sharply in space and is largest for young, skilled, and male workers.

Combining established identification strategies from labour, urban, and trade economics (Combes et al., 2008, 2019; Autor et al., 2013; Dauth et al., 2014) and exogenous variation originating from trade shocks, Germany's division period, and deep history, we then use our data set to estimate the key parameters of the model. Our model provides the microfoundations for a non-parametric migration gravity equation whose estimation reveals that the resistance to migrate increases sharply up to a distance of 200 km between origin and destination and much more moderately thereafter. Within origin-destination pairs, workers above the age of 30 have a migration resistance that is four times that of workers below the age of 30. Women have a resistance that is 65% higher than that of men. Compared to unskilled workers, skilled workers have a resistance that is between 65% (tertiary education) and 82% (apprenticeship) lower. These group-specific differences in migration resistance are attributable to differences in migration costs with one exception. Workers up to the age of 30 are relatively mobile but not particularly responsive to spatial differences in real wages. Within our model, this implies that idiosyncratic determinants such a marriage or other significant changes in personal circumstances are relatively more important drivers of migration. As for the agglomerative and congestive forces in the model, we estimate group-specific productivity elasticities of density that range from close to zero to about 0.035, with a weighted average of 0.018 with skilled, older, and female workers benefiting relatively more from agglomeration. The estimated density elasticity of housing costs is slightly below 0.2. The estimated density elasticity of regional amenity varies between zero and -0.095, with -0.0687 being the weighted average and density being a net-disamenity for skilled and older workers in particular. Given these parameter estimates and the observed values of the endogenous variables (employment, wages, housing costs, migration), there is a unique mapping to exogenous productivity, amenity.

Having identified the model, we use its structure to solve for the unobserved equilibrium values of the endogenous variables. An important insight from a comparison to a spatial equilibrium without migration costs is that migration costs lead to greater spatial concentration. Owing to density-biased migration costs, the

weighted average density in the economy is 37% higher, leading to 4% higher productivity and wages, 40% (unskilled) to 85% (high-skilled) higher housing costs, and 11%-34% lower housing consumption. These results are rationalized by a novel estimate of the density elasticity of in-migration cost of -0.2.

We then show how to use the spatial equilibrium with migration costs as a starting point for equilibrium-to-equilibrium evaluations of the causal effects of changes in exogenous variables on endogenous variables in general equilibrium. To illustrate the potential of our theoretical framework for the quantitative evaluation of the aggregate and distributional consequences of spatial shocks and policies, we present three applications. First, we evaluate the consequences of increasing trade exposure due to the rise of China and Eastern Europe. We model this shock as a change in region-group-specific exogenous productivity. Second, we analyze the effect of a change in the planning system by upgrading exogenous housing supply in former West Germany to the level of former East Germany where affordable was provided through a central planning system during the cold-war period and investments into the housing stock were heavily subsidized after Germany's unification. Third, we assess the consequences of a regional transfer similar to the *Solidaritätszuschlag* which was introduced in the aftermath of Germany's reunification to subsidize public services and capital investments in former East Germany. We model this policy as an increase in local public services in the east that is fully financed by an increase in the national income tax rate. In each case, we find welfare effects that are unevenly distributed across groups and regions. Once we account for migration costs, there are winning and losing workers within winning and losing regions, with the immobile worker groups (female, unskilled, older) being the most vulnerable. We conclude that in the presence of migration costs, the social cost-benefit analysis of a spatial policy requires an explicitly defined social welfare function.

We build on a large body of theoretical urban economics research in the tradition of Rosen (1979) and Roback (1982) and more recent quantitative spatial models such as Allen and Arkolakis (2014), Ahlfeldt et al. (2015), and Monte et al. (2018) that have assumed a spatial equilibrium. We take inspiration from McFadden (1974) and Eaton and Kortum (2002) to derive stochastic formulations of migration decisions. Our focus on migration costs is motivated by recent evidence on the economic cost of migration frictions (Bryan and Morten, 2019; Caliendo et al., 2019; Tombe and Zhu, 2019). Our main contribution is to develop a quantitative spatial model that does not assume but solves for the spatial equilibrium and can be used for transparent evaluations of spatial policies in general equilibrium under the *ceteris paribus* assumption, with and without migration costs. As such, we directly connect

to a growing literature concerned with the evaluation of place-based policies (Kline and Moretti, 2013; Blouri and Ehrlich, 2017; Ehrlich and Seidel, 2018; Fajgelbaum and Gaubert, 2018). Our contribution to this literature is to provide a quantitative framework in which place-based policies can have positive effects on localized utility owing to migration frictions.

In developing and identifying our model, we make a number of more specific contributions to a range of literature strands in labour and urban economics. We connect to a literature analyzing the labour-market-related causes (Kennan and Walker, 2011) and consequences (Monras, 2018) of migration. Our contribution is to develop a theoretical framework in which migration decisions are endogenous to labour market and housing market outcomes and vice versa. An emerging literature seeks to quantify the cost of migration (Bryan and Morten, 2019). Our contribution is to show that migration costs are a concave function of distance, implying that the average distance elasticity of migration cost is greater in smaller countries. Our model features labour-market related agglomeration effects on productivity which have been subject to a large empirical literature summarized in Combes and Gobillon (2015). Our contribution is to complement evidence on skill-biased returns to agglomeration (Baum-Snow and Pavan, 2013) by documenting age and gender gaps in agglomeration returns. Our model also features housing-market-related costs of agglomerating, which are being studied in an emerging literature (Combes et al., 2019). Our contribution is to provide the microfoundations for the inference of the housing supply elasticity from the output density elasticity of housing cost, which is relatively straightforward to estimate. Another strand to which we connect is concerned with the inference of quality of life from wages and housing costs (Albouy, 2015). Our contribution is to derive compensating differentials in the presence of migration cost and to provide group-specific estimates of the (dis)amenity value of a broad range of location characteristics, including density. The literature summarized by Ahlfeldt and Pietrostefani (2019) points to costs of agglomeration that exceed benefits for high levels of agglomeration, suggesting that the process of agglomeration naturally comes to an end, if only beyond the point of optimal density. Our contribution is to provide novel evidence on a density bias in migration costs which can rationalize ongoing growth of seemingly over-agglomerated areas.

To illustrate the model's potential for the quantitative evaluation of spatial shocks and policies, we choose applications that relate to topical research questions in trade, housing, and public economics. Autor et al. (2013) and Dauth et al. (2014) evaluate the local labour market effects of increasing trade exposure. A prominent literature analyses the causes (Saiz, 2010) and effects of housing supply

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constraints (Green et al., 2005), sometimes asking the question what would happen if regulatory constraints were relaxed (Hilber and Vermeulen, 2016). A large literature in the tradition of Tiebout (1956) and Oates (1969) estimates effects of local taxes and public expenditures on housing costs and residential sorting (Banzhaf and Walsh, 2008). In each case, the literature is centred on reduced-form evidence. Our contribution to these literatures is to show how general equilibrium effects in the spatial economy emerge through interactions on labour and housing markets, moderated by migration. In evaluating the aggregate and distributional consequences of these spatial events, we connect to a classic economics literature concerned with the aggregation of individual welfare in a social welfare function (Atkinson, 1970). Our contribution to this literature is to show how the social welfare function becomes more important in the evaluation of spatial phenomena, the larger migration costs are.

The remainder of the paper is structured as follows. Section B provides stylized facts of the spatial economy that motivate the structure of our model. Section C outlines the model. Section D provides an overview of our data. Section E identifies the structural parameters and the exogenous variables in the model. Section F solves for the spatial equilibrium with migration costs. Section G shows how to use the model for counterfactual analysis. Section H provides three applications of the model to the evaluation of spatial phenomena. Section I concludes.

B Stylized facts

To motivate the structure of the model developed in Section C, we first illustrate some stylized facts of a spatial economy in Figure 1 using data that we describe in Section D. The upper panels show how spatial concentration is associated with benefits due to agglomeration economies on labour markets (a) and costs due to congestion on housing markets (b). This descriptive evidence confirms conventional wisdom in urban economics that the cost of agglomeration must exceed the benefit, at least at the margin, for a stable system of cities to exist.

In the middle panels, we turn to determinants and consequences of migration that are central to the novel aspects of our model. There is a positive association between the average wage local labour market offers and the number of workers it attracts (c). At the same time there is a positive association between net in-migration into labour markets and changes in local housing cost (d). This descriptive evidence supports some important assumptions that are implicit to the spatial equilibrium framework and the idea of spatial arbitrage. First, workers are at least imperfectly

mobile and respond to economic incentives when making location decisions. Second, due to inelastic supply of land, migration into attractive destinations leads to mean reversion in the attractiveness of location and the well-known compensating differentials.

Yet, the bottom panels of Figure 1 reveal that workers are not perfectly mobile. The fraction of workers who migrate is generally low, despite significant variation across groups (e). Conditional on migrating, the propensity of a location becoming a migration destination declines rapidly in space (f). Motivated by these stylized facts, we model the causes and consequences of imperfect mobility in general equilibrium in the next section.

C   Model

Consider an economy that is populated by $\bar{L} = \sum_\theta L^\theta$ workers who we categorize in groups $\theta \in \Theta$ (e.g. according to age, gender, skill) and who supply one unit of labor inelastically. Individuals choose their place of residence and work across $i, j \in J$ regions, but migration from location i to j is costly. Each region is endowed with a measure $\bar{T}_i$ of land used for housing.

C.1   Workers

C.1.1   Preferences and demand

Individual ω belonging to group θ and living in region i derives utility from the consumption of a freely-tradable homogeneous good $(x_{i,t}^\theta(\omega))$, housing $(h_{i,t}^\theta(\omega))$ and amenities $(A_{i,t}^\theta, a_{ii,t}^\theta(\omega))$ according to

$$U_{i,t}^\theta(\omega) = \left(\frac{x_{i,t}^\theta(\omega)}{\alpha}\right)^\alpha \left(\frac{h_{i,t}^\theta(\omega)}{1-\alpha}\right)^{1-\alpha} A_{i,t}^\theta a_{ii,t}^\theta(\omega). \tag{1}$$

In anticipation of the empirical analysis, we include a time index t that helps us derive estimation equations from the theoretical model as detailed in the identification chapter E below. The Cobb-Douglas structure implies that individuals spend constant shares α and $1 - \alpha$ of their income on the tradable good and housing. Normalizing the price of the homogeneous good to unity, $p_{i,t}$ represents the relative

price of housing in location i. We then obtain the demand functions

$$x_{i,t}^\theta(\omega) = \alpha(1-\iota)w_{i,t}^\theta(\omega)$$
$$h_{i,t}^\theta(\omega) = \frac{(1-\alpha)(1-\iota)w_{i,t}^\theta(\omega)}{p_{i,t}}, \tag{2}$$

where ι denotes the federal income tax rate and $w_{i,t}^\theta(\omega)$ are gross wages for an individual ω in group θ in location i. Individuals' preferences for amenities are split into a group-specific component and an idiosyncratic part. The former is represented by

$$A_{i,t}^\theta = \bar{A}_{i,t}^\theta \left(\frac{L_{i,t}}{\bar{T}_i}\right)^{\zeta^\theta} \frac{G_t}{\bar{L}}, \tag{3}$$

where $\bar{A}_{i,t}^\theta$ is an exogenous part (such as climate), $L_{i,t}/\bar{T}_i$ is an endogenous part depending on employment density (e.g. theatres or congestion), and $G_t/\bar{L}$ represents equal per-capita public spending across locations where the federal government meets its budget constraint $G_t = \sum_i \sum_\theta \iota w_{i,t}^\theta L_{i,t}^\theta$. Notice that this implies transfers from high-income to low-income regions. To allow for heterogeneity in tastes and preference-based sorting, exogenous amenities $\bar{A}_{i,t}^\theta$ and the density elasticity of amenity ζ^θ are group-specific. Since density generates amenities and disamenties the sign of ζ^θ is theoretically ambiguous.[1] We model idiosyncratic amenity $a_{ij,t}^\theta(\omega)$ as bilateral stochastic shocks to allow for exogenous events that make a region j a closer substitute for home region i for group θ or shift a personal attachment of worker ω from i to j. For a worker remaining in i, the realization is simply $a_{ij=i,t}^\theta(\omega)$. We discuss the precise stochastic formulation when we model migration decisions in section C.3.

C.1.2   Worker productivity

Following the conventions in urban economics (Combes and Gobillon, 2015), we model the productivity of individuals, $\varphi_{i,t}^\theta(\omega)$, as dependent on location factors that are exogenous to our model (e.g. access to navigable rivers), endogenous agglomeration (employment density), and an individual effect that consists of time-invariant (innate skill) and time-varying (e.g. employment status) factors. In particular, we impose

$$\varphi_{i,t}^\theta(\omega) = \varphi_{i,t}^\theta \delta_{i,t}^\theta(\omega), \tag{4}$$

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[1]See Ahlfeldt and Pietrostefani (2019) for a synthesis of the evidence.

where $\delta_{i,t}^\theta(\omega)$ summarizes idiosyncratic determinants of productivity and the group-region productivity $\varphi_{i,t}^\theta$ depends on an exogenous component $\psi_{i,t}^\theta$ and and on density $L_{i,t}/\bar{T}_i$:[2]

$$\varphi_{i,t}^\theta = \psi_{i,t}^\theta \left(\frac{L_{i,t}}{\bar{T}_i} \right)^{\kappa^\theta}. \tag{5}$$

We assume that firms are only able to observe the average productivity per group, so we impose $\delta_{i,t}^\theta(\omega)$ to be a log-normally distributed error term of mean zero for the sake of simplicity. Prompted by evidence on skill-biased returns to agglomeration (Baum-Snow and Pavan, 2013), we allow the density elasticity of productivity $\kappa^\theta > 0$ to vary across groups. Similarly, each group is equipped with a location-specific exogenous productivity $\psi_{i,t}^\theta$ to capture any complementarity between skills and exogenous location factors, such as an airport that allows high-skilled workers to quickly travel to business meetings.

C.2 Firms

Firms produce the tradable good under perfect competition using labor as their only input. As the price serves as the numeraire, wages of group-θ workers in location i map directly into group-region productivity $\varphi_{i,t}^\theta$. Total output (equal to revenues and nominal income) in i is then given by $X_{i,t} = \sum_\theta L_{i,t}^\theta \varphi_{i,t}^\theta$.

Housing is supplied by profit-maximizing developers operating under perfect competition according to a Cobb-Douglas production function combining a share of the globally available capital stock with location-specific land:

$$H_{i,t}^S = \eta_{i,t} \left(\frac{\bar{T}_i}{\beta} \right)^\beta \left(\frac{K_{i,t}}{1-\beta} \right)^{1-\beta}, \tag{6}$$

where $K_{i,t}$ is the capital used in region i and $\eta_{i,t}$ denotes total factor productivity (TFP), capturing the role of regulatory (e.g. height regulations) and physical (e.g. a rugged surface) constraints (Saiz, 2010). While developers make zero profits, we assume that the owners of employed capital and land are absent so their income is irrelevant for local demand.

In equilibrium, aggregate housing demand will equal aggregate housing supply

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[2]The idiosyncratic components of productivities push up the level of wages and utility in our model, but do not influence migration decisions as individuals care only about the *increase* in indirect utility associated with a move to another destination. In our empirical analysis, we back out the idiosyncratic components of individuals' wages in a wage decomposition à la Abowd et al. (1999) (henceforth AKM)and proceed with the group-time-destination-specific wage component.

in each region i which delivers[3]

$$p_{i,t} = \left(\frac{(1-\alpha)\beta(1-\iota)X_{i,t}}{\eta_{i,t}^{\frac{1}{\beta}}\bar{T}_i} \right)^{\beta}.$$ (7)

This formulation implies that both capital input and housing prices are increasing in housing expenditure, and that $p_{i,t}$ is lower in locations with more land supply and higher TFP ceteris paribus. Note that because wages depend on $L_{i,t}$, equation (7) can be rearranged to express $p_{i,t}$ as a function of $\eta_{i,t}$ and employment density $L_{i,t}^{\theta}/\bar{T}_i$. Thus, the housing price establishes an important dispersion force in our model as long as κ^{θ} is small relative to β (see appendix for details).

C.3 Migration and timing

It is conventional in spatial economics to assume that free migration leads to perfect long-run spatial arbitrage. Unlike in the standard spatial equilibrium framework (Roback, 1982), we model the process of residential location choice explicitly, allowing for positive migration costs. To this end, we connect the utility a worker derives at a potential migration destination j to the migration origin i via two channels.

First, a move from i to j implies migration costs modeled as a utility discount of $(\exp[\tau_{ij}^{\theta}])^{-1}$ with $\tau_{ij}^{\theta} \geq 0$.[4] We think of migration costs as loss of social capital that depends on the interaction of distance on the one hand and age, gender, and skills on the other.[5] Thus, bilateral migration costs are group-specific in our model and assumed to be time-invariant.

Second, we assume that in each time period, workers receive idiosyncratic amenity shocks, $a_{ij,t}^{\theta}(\omega)$, that are i.i.d. across locations, individuals, and time and follow a stochastic process going back to McFadden (1974).[6] In each period, every individual located in region i, draws an amenity value for every location j from a Fréchet distribution

$$F_{ij,t}^{\theta}(a) = e^{-B_{ij,t}^{\theta}a^{-\gamma^{\theta}}} \qquad \forall \ \theta \ \text{ and } \ \gamma^{\theta} > 1,$$ (8)

where the group-specific shape parameter γ^{θ} governs the dispersion of amenities,

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[3]We have normalized the world price for capital to unity. See appendix for details.

[4]Migration costs do not occur if workers stay in the same region, so $\tau_{ii}^{\theta} = 0$.

[5]Distance here is interpreted broadly: additionally to geographical distance it could include cultural distance like in Falck et al. (2012) or political distance. See Glaeser et al. (2002) for evidence on the determinants of social capital.

[6]This approach is established in the literature and has been applied to describe productivity distributions, e.g. as in Eaton and Kortum (2002), or individual preferences, e.g. as in Monte et al. (2018).

with larger values implying lower dispersion and less "amenity heterogeneity". $B_{ij,t}^\theta$ denotes the time-varying, group-specific average of these shocks (bilateral amenity, scale parameter) and is normalized to have mean of one. Following the mixed multinomial logit model of discrete response (MMNL) (McFadden and Train, 2000), workers with the same observable characteristics (age, gender, skill) face similar distributions of unobservable amenity shocks, but the shape and scale parameters of amenity shocks differ across groups. Idiosyncratic amenity is conceptionally important and essential for the tractability of the model. It captures common trends such as downtown gentrification that make specific pairs of locations closer substitutes for certain groups in certain periods. This is important to rationalize migration flows that vary over time within groups and bilateral region pairs even if prices, wages, and migration costs remain constant. Idiosyncratic amenity also captures changes in personal circumstances in i (e.g. a divorce) that interact with events at j (e.g. a new romance).[7] As a result, individuals of the same group make different location decisions despite facing the same regional price, wage and amenity, rationalizing imperfect spatial sorting.

Our approach to modelling migration decisions draws from financial economics. Intuitively, we model migration as an investment decision in which expected returns in the form of utility flows are traded against a one-off sunk cost of rebuilding social capital at a potential destination. At the end of period t, individuals receive amenity shocks and realize their location-specific utility at the place of residence. The migration decision takes place at the beginning of the next period based on observed utility levels obtainable in all J locations. Time is discrete and we assume that workers are myopic. This means that they extrapolate their current amenity shock realizations as well as observed wages and prices to all future periods and compare their achievable net present values (NPV) at the beginning of period $t+1$. Formally, we have

$$NPV_{ij|i,t+1}^\theta(\omega) = \max_{j \in J} V_{j|i,t}^\theta(\omega) m_{ij}^\theta = \max_{j \in J} \frac{(1-\iota) w_{j,t}^\theta A_{j,t}^\theta a_{ij,t}^\theta(\omega)}{\left(p_{j,t}^h\right)^{1-\alpha}} m_{ij}^\theta, \qquad (9)$$

where indirect utility in j conditional on living in i, $V_{j|i,t}^\theta(\omega)$, is regarded as a flow of utility that depends on observables in period t and

$$m_{ij}^\theta \equiv \frac{1}{1+\rho} \left[\frac{1}{\exp(\tau_{ij}^\theta)} + \frac{(1+\rho)^{\mathcal{T}^\theta-1} - 1}{\rho(1+\rho)^{\mathcal{T}^\theta-1}} \right] > 1 \qquad (10)$$

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[7]Positive amenity shocks in a destination j imply higher utility increases when they occur close to current worker location i, making it less costly for individuals to leverage them.

is the migration-cost adjusted annuity multiplier of indirect utility that consists of three components:[8] First, migration costs τ_{ij}^{θ} deflate utility in the first period after a relocation in which a worker has to rebuild social capital. Second, the time-preference monitored by the discount rate ρ determines how a future utility flow in period $t + k$ is weighed against the migration cost in period $t + 1$. Third, $\mathcal{T}^{\theta}$ governs the group-specific number of periods of the annuity. As an example, younger workers have a higher propensity to relocate as shown in Figure 1 and may, therefore, expect to remain fewer years at a migration destination. Our general formulation of the annuity multiplier nests the well-known special case $m_{ij}^{\theta} = 1/\rho$ if there are no migration costs ($\tau_{ij}^{\theta} = 0$) and there is an infinite time horizon ($\mathcal{T}^{\theta} \to \infty$). In keeping with intuition, the multiplier m_{ij}^{θ} is larger for smaller bilateral migration costs τ_{ij}^{θ}, implying a greater migration incentive for a given indirect utility $V_{j|i,t}^{\theta}(\omega)$. If a destination j is attractive due to a high $V_{j|i,t}^{\theta}(\omega)$, migration incentives will be larger if the discount rate ρ is small and the time horizon $\mathcal{T}^{\theta}$ is large because future utility gains carry a larger weight relative to contemporaneous migration costs. After the migration decision has been made, workers realize their utility in their new location (which can, of course, be equal to the old location) and the procedure starts over again.

Importantly, the distributional assumption regarding individual amenities implies that indirect utility also follows a Fréchet distribution with a group-specific shape parameter γ^{θ}. This enables us to derive the conditional probability that a worker from group θ migrates from i to j as

$$\chi_{ij|i,t}^{\theta} = \frac{B_{ij,t}^{\theta} \left(A_{j,t}^{\theta} w_{j,t}^{\theta} (p_{j,t})^{\alpha-1} m_{ij}^{\theta}\right)^{\gamma^{\theta}}}{\sum_{n \in J} B_{in,t}^{\theta} \left(A_{n,t}^{\theta} w_{n,t}^{\theta} (p_{n,t})^{\alpha-1} m_{in}^{\theta}\right)^{\gamma^{\theta}}}. \tag{11}$$

Notice that $\chi_{ij|i,t}^{\theta}$ is increasing in amenities and wages in the destination market and decreasing in house prices and bilateral migration costs. At the same time, the probability of migrating from i to j is decreasing in wages and amenities and increasing in house prices and migration costs of all other regions via the denominator. This term is analogous to the "multilateral resistance term" used in gravity equations of international trade. Further, the impact of the annuity multiplier m_{ij}^{θ} on migration probabilities $\chi_{ij|i,t}^{\theta}$ increases in individual amenity heterogeneity monitored by γ^{θ} as workers become more attached to specific regions. We term the joint effect of m^{θ} and γ^{θ} "migration resistance". Since all workers migrate to a destination in period t (which can be the origin), aggregate employment in region i in $t+1$ equates to the

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[8]See the appendix for derivation details. In contrast to our approach, Caliendo et al. (2019) assume perfect foresight so individuals form expectations about future amenity shocks and prices.

sum of inflows $M_{ji,t}^{\theta}$ from all locations j:

$$L_{i,t+1}^{\theta} = \sum_{j \in J} M_{ji,t}^{\theta} = \sum_{j \in J} \chi_{ji|j,t}^{\theta} L_{j,t}^{\theta} \qquad (12)$$

Using equation (9), we can compute the expected lifetime utility in location i discounted in time and migration costs for all groups and migration origins at any time as:

$$\mathcal{U}_{i,t}^{\theta} = E[NPV_{ij|i,t}^{\theta}] = \Gamma\left(\frac{\gamma^{\theta} - 1}{\gamma^{\theta}}\right)\left[\mathcal{V}_{i,t}^{\theta} + \mathcal{O}_{i,t}^{\theta}\right]^{\frac{1}{\gamma^{\theta}}} \qquad (13)$$

$$\text{with } \mathcal{V}_{i,t}^{\theta} = B_{ii,t}^{\theta}\left(A_{i,t}^{\theta}(1-\iota)w_{i,t}^{\theta}\,(p_{i,t})^{\alpha-1}\,m_{ii}^{\theta}\right)^{\gamma^{\theta}} \quad \text{and}$$

$$\mathcal{O}_{i,t}^{\theta} = \sum_{j \neq i \in J} B_{ij,t}^{\theta}\left(A_{j,t}^{\theta}(1-\iota)w_{j,t}^{\theta}\,(p_{j,t})^{\alpha-1}\,m_{ij}^{\theta}\right)^{\gamma^{\theta}}$$

Expected net-utility increases in the utility a region i offers, and decreases in the migration cost at which the utility other regions j offer can be accessed. Intuitively, $\mathcal{O}_{i,t}^{\theta}$ captures a migration option value. The potential to migrate to attractive destinations at low cost provides an insurance against negative spatial shocks. Equation (13) entails perfect utility equalization assumed in the conventional spatial equilibrium as a special case with $\Theta = 1$ (one worker group) and $\tau_{ij,t}^{\theta} = 0$ (no migration costs).

C.4 Spatial general equilibrium

One of our key contributions is to develop a theoretical framework in which the conventional assumption of a spatial economy being in equilibrium can be relaxed. Since we allow for arbitrary shocks to exogenous productivity, regional and bilateral amenity, and housing TFP, an observed economy may, but most likely will not be in spatial equilibrium. Migration as modeled in section C.3, however, works towards restoring an equilibrium. Intuitively, shocks to exogenous variables $\{\psi_{i,t}^{\theta}, \eta_{i,t}, \bar{A}_{i,t}^{\theta}, B_{ij,t}^{\theta}\}$ affect expected net-utility directly or indirectly. For example, a positive shock to labour productivity maps into higher wages $w_{i,t}^{\theta}$ according to equation (5) due to perfect competition on goods and labour markets and the choice of the tradable good as the numeraire. Likewise, a positive shock to housing TFP maps into lower housing costs $p_{i,t}$ according to (7) due to perfect competition among developers. Higher $w_{i,t}^{\theta}$ and lower $p_{i,t}$ affect bilateral migration probabilities $\chi_{ij|i,t}^{\theta}$ according to (11), leading to in-migration. Given (12), this results in endogenous changes in employment which in turn determine changes in endogenous amenity, wages (due

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to agglomeration economies) and housing costs (due to inelastically provided land). As long as agglomeration costs exceed agglomeration benefits at the margin, the consequence of migration is to reduce the differences in expected net-utility that cause migration.

We conceptualize a spatial equilibrium with migration costs as a counterfactual situation to which the spatial economy would converge due to migration-induced spatial arbitrage if there were no further shocks to exogenous variables. This entails a migration equilibrium in which the sum of outflows equals the sum of inflows for each location. This condition reads

$$\sum_{j \in J} \chi^{\theta}_{ij|i,t} L^{\theta}_{i,t} = \sum_{j \in J} \chi^{\theta}_{ji|j,t} L^{\theta}_{j,t} \qquad \forall \ j \in J, \theta \in \Theta. \tag{14}$$

Notice, that our model implies bilateral migration even in equilibrium because individuals receive idiosyncratic amenity shocks in every period. Finally, the labor endowment constraint determines the level of welfare, so we impose the labor market clearing conditions

$$\bar{L}^{\theta}_t = \sum_{i \in J} L^{\theta}_{i,t} \tag{15}$$

with the economy-wide labor endowment $\bar{L}_t = \sum_{\theta} \bar{L}^{\theta}_t$.

Unlike in a model with free mobility where the spatial equilibrium is essentially assumed, the identification of the spatial equilibrium with migration costs is a critical step for the counterfactual analysis of the effects of spatial shocks and policies. Given the primitives of the model, we take parameters $\{\alpha, \beta, \rho, \gamma^{\theta}, \zeta^{\theta}, \kappa^{\theta}\}$ and the vector of exogenous variables $\{\psi^{\theta}_{i,t}, \eta_{i,t}, \bar{A}^{\theta}_{i,t}, \tau^{\theta}_{ij,t}, B^{\theta}_{ij,t}\}$ as given and seek the equilibrium vector $L^{\theta}_{i,t}{}^*$ that solves the following system of equations: housing-market clearing (7), the migration condition (14), and labor-market clearing (15). From $L^{\theta}_{i,t}{}^*$, there is a unique mapping to equilibrium productivity $\varphi^{\theta}_{i,t}{}^*$ according to (5), to equilibrium housing costs $p_{i,t}{}^*$ according to (5) and (7), and into endogenous amenity $A^{\theta}_{i,t}{}^*$ according to (3). Hence, equilibrium migration probabilities $\chi^{\theta}_{ji|j,t}{}^*$ are also determined by $L^{\theta}_{i,t}{}^*$ according to (3), (5), (7), and (11). We show in the appendix that for plausible parameter values there is a unique spatial equilibrium for any given values in exogenous variables.

D   Data description

To identify the critical model parameters and the exogenous variables, we require four sets of data compiled for consistent units of spatial analysis: Employment,

wages, floor space prices, and bilateral migration. In addition, we have compiled data on trade shocks to construct instrumental variables, and data on determinants of migration costs as well as proxies for location fundamentals for overidentification tests. A summary of our data is below, complemented by a more detailed description in the appendix.

D.1 Spatial unit

As an empirical correspondent to locations indexed by i in the model we choose the 141 German labour market regions defined by Kosfeld and Werner (2012). The delineation of these areas is based on combining one or more administrative regions at the county level with the aim of creating self-contained labour markets. This is done by taking account of commuting flows between counties in a way that commuting within labour market regions is relatively large compared to commuting between regions (subject to an upper limit on commuting time of 45-60 minutes).

D.2 Employment

Our measure of employment $L_{i,t}^{\theta}$ is constructed from the Employment History (BeH) covering the years 1993-2017.[9] This dataset is provided by the Institute of Employment Research (IAB) and contains information on the universe of employees in Germany (with the exception of civil servants and the self-employed) on a daily basis. We only select those workers who are employed subject to social security contributions (including apprentices) and who are aged between 16 and 65 years.[10]

Based on this selection we compute the number of employees in each year and labour market region. In addition, we compute region-year-specific employment levels for different groups which are defined according to the interactions between sex, 3 skill categories (no apprenticeship, completed apprenticeship and tertiary education) and 3 age categories (16-30 years, 31-50 years and 51-65 years). Employment size varies considerably between labour market regions. While the average number of employees stands at 124,000 in the year 2017, values range from 16,000 in the labour market region *Vulkaneifel* to 1.4 million in *Berlin*.

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[9] We use version 10.03.02-180818.

[10] We extract all relevant information from the employment record that contains 30 June of a given year. If a person has multiple employment records, we select according to 1) the average daily wage, 2) the duration of the employment record, 3) at random.

D.3 Migration

We assign workers to labour market regions using their place of employment as reported in the BeH. Bilateral group-specific migration flows are then constructed by computing the number of workers belonging to group θ who used to be employed in region i in year t but who are working in region j in year $t+1$ for every pair of origin region i and destination region j. Based on these bilateral flows we construct group-specific migration probabilities $\chi_{ij,t}^{\theta}$ that are defined as the ratio of the flows and the level of employment in origin region i in year t. Since labour market regions are designed with the aim of reflecting commuting patterns in a region, we propose that a change in the place of employment across labour market regions is likely to go along with a change of residence.[11]

D.4 Productivity

In line with the standard approach in the agglomeration literature (Combes and Gobillon, 2015), we assume in (4) that worker productivity $\varphi_{i,t}^{\theta}(\omega)$ is a multiplicative function of a group-regional-year component $\varphi_{i,t}^{\theta}$ and an individual component $\delta_{i,t}^{\theta}(\omega)$. Following the conventions in labour economics (Abowd et al., 1999), we define $\delta_{i,t}^{\theta}(\omega) = \exp(\bar{\delta}_{\omega} S_{i,t}^{L} z^{L} f_{i,\omega,t}^{L,\theta})$ as a function of unobserved time-invariant individual productivity $\bar{\delta}_{\omega}$ (we use ω as a subscript to index workers), observable worker characteristics $S_{\omega,t}^{L}$ (dummies for whether a worker is in an apprenticeship or works part-time, with z^{L} being the marginal effects) and a stochastic residual term $f_{i,\omega,t}^{L,\theta}$. Log-linearization and setting individual productivity equal to the nominal wage $\varphi_{i,t}^{\theta}(\omega) = w_{i,\omega,t}^{\theta}$ as predicted under perfect competition (see C.2) then gives the estimation equation:

$$\ln w_{i,\omega,t}^{\theta} = \bar{\delta}_{\omega} + S_{i,t}^{L} z^{L} + \tilde{\varphi}_{i,t}^{\theta} + f_{i,\omega,t}^{L,\theta}. \tag{16}$$

To remove a common national trend, we run an auxiliary regression of $\tilde{\varphi}_{i,t}^{\theta}$ against region effects and year effects and subtract the latter. Our destination-group-time-specific productivity index is defined as $\varphi_{i,t}^{\theta} = \exp(\tilde{\varphi}_{i,t}^{\theta})$. To estimate equation (16), we use matched employer-employee data including nominal wages from the IAB covering the universe of German workers and establishments from 1993 to 2017.

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[11]This assumption is backed up by a considerable degree of overlap between the place of employment and the place of residence. For the year 2017, we find that approximately 75% of employees who work in a specific labour market region also live there. Moreover, use of the place of residence would reduce the available data as this information is only available from 1999 onward.

D.5 Housing costs

In line with standard practice in urban economics, we model the cost of housing as a rental price whereas in our data we observe purchase prices. Following conventions, we assume that property markets are competitive and investors and owner-occupiers apply the $\rho = 0.05$ discount rate to future streams of actual or imputed rents over an infinite horizon. Our empirical measure of rent then is $p_{i,t} = 0.05 P_{i,t}$, where $P_{i,t}$ is a location-time-specific house price index following Combes et al. (2019), who in turn build on a long tradition of urban gradient regressions going back to Clark (1951):

$$\ln P_{s,i,t} = \ln D_{s,i}^P u_i + \tilde{S}_{s,i,t}^P z_i^P + \tilde{P}_{i,t} + f_{s,i,t}^P, \tag{17}$$

where $\ln P_{s,i,t}$ is the log of price per square meter floor area of property s, $\ln D_{s,i}^P$ is a vector of location-specific variables that capture distance from the geographic centroid of the municipality with the largest employment in a labour market area, u_i are the destination-specific gradients, $\tilde{S}_{s,t} = S_{s,t} - \bar{S}$ is a vector of property characteristics $S_{s,t}$ (see appendix section L.3 for details) net of the national average $\bar{S}$, z_i^P is a vector of destination-specific implicit prices, $\tilde{P}_{i,t}$ is a location-year fixed effect and $f_{s,i,t}^P$ is an unobserved residual. To remove a common national trend, we run an auxiliary regression of $\tilde{P}_{i,t}$ against region effects and year effects and subtract the latter. From the adjusted location-year fixed effect we infer a property price index $P_{i,t} = e^{\tilde{P}_{i,t}}$, which is mix-adjusted for property characteristics and location and representative for a property with the national average characteristics at the centre of a labour market area. Our property micro data is from Immoscout24 covering more than 16.5 million sales proposals for apartments and houses between 2007-2017.[12]

D.6 Import and export exposure

As discussed in the identification section, we require instrumental variables that predict wage shocks, but are uncorrelated with shocks to housing productivity and amenities. Below, we define the measures of import exposure IE_t^d and export exposure EE_t^d which we borrow from Dauth et al. (2014). Both instrumental variables exploit the rise of China and Eastern Europe (CE) in the world economy. The exposure of a German region depends on the imports (IMP) or exports (EXP) of China and Eastern Europe in industry sectors indexed by q and the relative importance of these sectors for a German region. To avoid a validity problem due to endogenous

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[12]See appendix for details. The data were accessed via the FDZ-Ruhr (Boelmann and Schaffner, 2019).

trade flows, we consider flows between China and Eastern Europe and a group of other countries excluding Germany. This group (OTHER) includes the following countries: Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom. We have

$$IE_{it}^d = \sum_q^Q \frac{\bar{E}_{iq}}{\bar{E}_q} \frac{IMP_{c,t}^{CE \to OTHER}}{\bar{E}_i} \tag{18}$$

$$EE_{it}^d = \sum_q^Q \frac{\bar{E}_{iq}}{\bar{E}_q} \frac{EXP_{q,t}^{OTHER \to CE}}{\bar{E}_i}, \tag{19}$$

where $\bar{E}$ is the time-invariant initial value of employment, $IMP_{q,t}^{CE \to OTHER}$ are the imports of other countries from China and Eastern Europe in sector q, and $EXP_{q,t}^{OTHER \to CE}$ are the respective exports from other countries to China and Eastern Europe. The logic behind these instruments is that the rise of China and Eastern Europe also leads to higher bilateral trade volumes in other countries that are arguably uncorrelated with shocks in Germany that affect German trade with China and Eastern Europe.

D.7 Migration distance

We identify the centre of a labour market area as the municipality with the largest number of workers. We then compute the great circle distance between all labour market area centres as a geographic distance measure. For a cultural distance measure, we use a re-scaled version of the county-based dialect similarity index by Falck et al. (2012), which we aggregate to labour markets.

D.8 Fundamentals

We compute a comprehensive data set on fundamental first-nature characteristics that potentially affect productivity (e.g. access to navigable rivers), amenity (e.g. climate), and housing TFP (e.g. physical constraints to development).

E Identification

To solve for the spatial equilibrium discussed in C.4, we require values for parameters $\{\alpha,\ \beta,\ \rho,\ \gamma^\theta,\ \zeta^\theta,\ \kappa^\theta\}$ and exogenous variables $\{\psi_{i,t}^\theta,\ \eta_{i,t},\ \bar{A}_{i,t}^\theta,\ \tau_{ij,t}^\theta,\ B_{ij,t}^\theta\}$. For identification, we use values of the endogenous variables $\{L_{i,t}^\theta,\ w_{i,t}^\theta,\ p_{i,t},\ \chi_{ij|i,t}^\theta\}$ observed in the data, which, unlike in models assuming a spatial equilibrium, may

differ from the equilibrium values $\{L_{i,t}^{\theta}{}^{*},\, w_{i,t}^{\theta}{}^{*},\, p_{i,t}^{*},\, \chi_{ij|i,t}^{\theta}{}^{*}\}$ which we solve for using the structure of the model as shown in F.1 below.

We set the housing expenditure share to $1 - \alpha = 0.33$, which is in line with a literature summarized in Ahlfeldt and Pietrostefani (2019) and official data (Statistisches Bundesamt, 2017). We use a tax rate of $\iota = 0.49$ which incorporates social insurance contributions that are proportionate to income in Germany (OECD, 2017). Likewise, we set the intertemporal discount rate to $\rho = 0.05$ following the literature on social cost benefit analysis (de Rus, 2010). Values for all other parameters as well as all exogenous variables are identified from our data using the structure of the model and the identification strategy discussed below.

E.1   Bilateral migration resistance ($\gamma^{\theta} m_{ij}^{\theta}$)

A log-linearized version of equation (11) provides the micro foundations for a non-parametric reduced-form migration gravity equation:

$$\ln \left(\frac{M_{ij,t}^{\theta}}{L_{i,t}^{\theta}} \right) = c^{\theta} + O_{i,t}^{\theta} + D_{j,t}^{\theta} + \tilde{m}_{ij}^{\theta} + \tilde{B}_{ij,t}^{\theta}, \tag{20}$$

where empirically we measure the migration probability $\chi_{ij,t}^{\theta} = M_{ij,t}^{\theta} / L_{i,t}^{\theta}$ as the ratio of the number of workers leaving region i for region j, $M_{ij,t}^{\theta}$, over the number of workers in i in year t, $L_{i,t}^{\theta}$. $D_{j,t}^{\theta} = \gamma^{\theta} \ln(A_{j,t}^{\theta} w_{j,t}^{\theta} (p_{j,t})^{\alpha-1})$ is a destination-year effect capturing migration pull factors, $O_{j,t}^{\theta} = \gamma^{\theta} \ln(\sum_{n \in J} (A_{n,t}^{\theta} w_{n,t}^{\theta} (p_{n,t})^{\alpha-1} m_{in,t}^{\theta}]))$ is an origin-year effect capturing multilateral resistance, $\tilde{m}_{ij}^{\theta} = \gamma^{\theta} \ln m_{ij}^{\theta}$ is an origin-destination effect with the theory-consistent restriction $\tau_{ij=i}^{\theta} = 0$ capturing bilateral migration resistance that depends on migration costs τ_{ij} and the variance of idiosyncratic shocks γ^{θ}, and $\tilde{B}_{ij,t} = \ln B_{ij,t}$ is a structural residual capturing bilateral amenity. $O_{i,t}^{\theta}$ and $D_{j,t}^{\theta}$ are identified up to a group-specific constant c^{θ}.

Following the conventions in the international trade literature on gravity equations we estimate equation (20) using a Poisson Pseudo Maximum Likelihood estimator (Head and Mayer, 2014). The non-parametric nature of equation (20) implies that we require no identifying assumption other than that group-specific shocks to bilateral amenity $B_{ij,t}^{\theta}$ are random within origin-destination pairs. Specification (20) is empirically demanding in that estimation requires sizable variation in migration over time within origin-destination pairs. In estimating equation (20), we leverage on the large differences in real wages and the consequently large migration flows between the formerly separated parts of Germany that initially persisted after unification but decreased substantially in the aftermath of unification.

In Figure 2, we present the distribution of the estimated migration resistance effects $\gamma^\theta \ln m_{ij}^\theta = \tilde{m}_{ij}^\theta$ by group and geographic distance. These reduced-form effects control for arbitrary migration push and pull factors and provide first evidence on which groups exhibit the largest resistance to migration, either because they face large migration costs (reflected in a large τ_{ij}^θ), or because they have few idiosyncratic reasons to migrate (reflected in a large γ^θ). Migration resistance increases sharply up to a distance of 200 km, a plausible limit for weekend commutes. Beyond 200 km, migration resistance increases at a slower rate. The differences in migration resistance across groups are also quantitatively important as revealed by the results from a regression of the estimated resistance parameters against categorical group identifier variables presented in Column (1) of Table 1. The migration resistance of old workers (age between 51 and 65 years) is almost four times that of young workers (aged 16-30). Likewise, women have a 65% higher migration resistance than men. In contrast, skilled (apprenticeship) and high-skilled (tertiary education) workers' migration resistance is 82% and 65% lower than for unskilled workers (no apprenticeship).

E.2 Individual amenity heterogeneity (γ^θ)

To recover the group-specific Frechet shape parameter γ^θ, we analyze the destination-year effects from (20) in the following empirical specification:

$$D_{j,t}^\theta = \gamma^\theta \ln W_{j,t}^\theta + \bar{e}_j^{d\theta} + e_{j,t}^{d\,\theta}, \tag{21}$$

where $W_{j,t}^\theta = w_{j,t}^\theta (p_{j,t})^{\alpha-1}$ and $\tilde{e}_j^{d\theta} + e_{j,t}^{d\,\theta} = \gamma^\theta \ln A_{i,t}^\theta$ is a structural residual capturing exogenous amenity through a fixed-effect component $\bar{e}_j^{d\theta}$ and a time-varying component $e_{j,t}^{d\,\theta}$. Intuitively, we identify γ^θ from this specification because a high real wage at j, ceteris paribus, leads to a greater migration flow if workers are less attached to locations due to idiosyncratic reasons, i.e. there is less dispersion in amenity shocks.

In estimating Equation (21), there is an identification challenge in that shocks to exogenous amenity $\bar{A}_{i,t}^\theta$ that enter $e_{j,t}^{d\,\theta}$ may be correlated with shocks to exogenous productivity $\varphi_{i,t}^\theta$ which enter $W_{j,t}^\theta$. As an example, a new highway will impact on productivity and amenity if it improves access to agglomeration and recreational space. To address this concern, we construct Bartik-style shift-share measures of rising import and export exposure to globalization shocks following the trade literature (Autor et al., 2013; Dauth et al., 2014). Adopting the theoretical argument from the literature, we use these measures as instrumental variables that predict local economic performance via changes in import pressure and export opportunities that

depend on the local industry mix. We argue that these trade-related instrumental variables are unlikely correlated with shocks to exogenous amenity. A detailed discussion of the exposure measures is in the data section.

Our estimates of γ^θ are in Figure 4. Consistent with theoretical expectations, all estimated parameters exceed unity, but there is heterogeneity. The results of a regression of the estimated amenity heterogeneity parameter against categorical group identifier variables presented in Column (2) of Table 1 reveals that our γ^θ estimates are about twice as large for workers above the age of 30 than for workers below that age. The implication is that idiosyncratic reasons are more important migration determinants for younger workers.

E.3 Bilateral migration cost (τ_{ij}^θ)

Having estimated (20) and (21) it is straightforward to recover migration costs for given values of ρ and $\mathcal{T}^\theta$ using (10) and $\ln m_{ij}^\theta = \tilde{m}_{ij}^\theta / \gamma^\theta$:

$$\exp(\tau_{ij}^\theta) = \frac{\rho}{\exp(\frac{\tilde{m}_{ij}^\theta}{\gamma^\theta})\rho(1+\rho) + (1+\rho)^{-(\mathcal{T}^\theta - 1)} - 1}, \qquad (22)$$

where we use the inverse of the relocation propensities displayed in Figure 1 as empirical proxies for $\mathcal{T}^\theta$. Intuitively, after adjusting for taste heterogeneity captured by γ^θ, the resistance to migrate m_{ij}^θ is determined by migration costs $\exp(\tau_{ij}^\theta)$ and the period $\mathcal{T}^\theta$ over which these are recovered via discounted (at rate ρ) utility flows.

In Column (3) of Table 1, we regress the estimated migration cost parameters against categorical group identifier variables. The results reveal that the relative resistance of female workers to migrate is driven by higher migration costs. Similarly, the lower migration resistance of skilled workers is due to lower migration costs. Interestingly, the greater migration resistance of older workers does not originate from greater migration costs but from limited idiosyncratic reasons to migrate.

E.4 Regional productivity $(\kappa^\theta, \psi_{i,t}^\theta)$

Our empirical approach to the identification of exogenous and endogenous productivity effects is inspired by Combes et al. (2008). We use a conventional AKM-regression described in the data section D.4 to separate the group-region-year specific component of productivity $\varphi_{i,t}^\theta$ defined in (5) from the worker-specific component. Next, we define the exogenous group-region-year productivity as $\psi_{i,t}^\theta = \exp(a_g^{L,\theta} + e_{i,t}^{L,\theta})$, where $a_g^{L,\theta}$ is a group-zone specific effect and $e_{i,t}^{L,\theta}$ is a structural residual. Zone effects capture differences in exogenous productivity between former East Germany

and West Germany, indexed by g, due to persistent effects of the division period. Log-linearization yields the following group-specific regression model, which exactly identifies the group-specific density elasticity of productivity κ^θ and the exogenous group-region-year productivity $\psi_{i,t}^\theta$:

$$\ln \varphi_{i,g,t}^\theta = a_g^{L,\theta} + \kappa^\theta \ln \left(\frac{L_{i,t}}{\bar{T}_i} \right) + e_{i,g,t}^{L,\theta}. \tag{23}$$

Unobserved fundamentals correlated with density pose a threat to identification of κ^θ. Following Ciccone and Hall (1996), we use the deep lag of log population density (1907) as an instrument for the log of contemporary density, arguing that fundamentals that gave rise to density a century ago are of limited relevance for productivity today. Since the instrumental variable is time-invariant, we cluster standard errors on regions.

The resulting estimates of the density elasticity of productivity are presented in Figure 3. The employment-weighted average estimate for κ is 0.018, close to the consensus of about 0.02 in the literature (Combes and Gobillon, 2015). There is significant heterogeneity across worker groups, with κ^θ estimates ranging from close to zero for young male workers to 0.035 for skilled and experienced female workers. In line with skill-biased returns to agglomeration (Baum-Snow and Pavan, 2013), we generally obtain greater κ^θ estimates for groups with higher skills. There is also a systematic gender gap in κ^θ favoring women, implying a greater gender pay gap in rural areas. Finally, young groups benefit little from agglomeration, suggesting that the productivity advantage associated with urban density materializes through an interaction with experience. An econometric analysis of the conditional variation in κ^θ estimates across groups is in Column (4) of Table 1.

E.5 Regional housing costs ($\eta_{i,t}$, β)

We use a similar approach as in E.4 to identify the exogenous and endogenous determinants of housing costs. We define exogenous housing TFP as $\eta_{i,t} = -\exp(\tilde{a}_g^P + e_{i,t}^P)$, where $\tilde{a}_g^P$ captures zone-specific legacy effects from the division period and $e_{i,t}^P$ is a structural residual. Log-linearization of equation (7) then yields the empirical specification:

$$\ln p_{i,g(i),t} = a_g^P + \beta \ln \left(\frac{X_{i,t}}{\bar{T}_i} \right) + e_{i,g(i),t}^P, \tag{24}$$

where $a_g^P = \beta \ln (1-\alpha)\beta(1-\iota) + \tilde{a}_g^P$ collects all scalars in (7) and the effects of zone-specific housing TFP. Given calibrated values for α and ι and an estimated value for β, exogenous housing TFP is uniquely identified as $\eta_{i,t} = ((1-\alpha)\beta(1-$

$\iota))^\beta (X_{i,t}/\bar{T}_i)^\beta / p_{i,t}$. To address the concern that contemporary productivity shocks may be correlated with output and housing TFP, we use the deep lag of population density as an instrument for output density and cluster standard errors on regions.

In column (1) in Table 2 we obtain an estimate of the output elasticity of housing costs β of 0.18. Note that because in our framework productivity varies across locations, there is a density-induced demand-side effect on wages in addition to the supply-side effect of employment density on housing costs that arises because of inelastically supplied land (see appendix section K.1 for a formal derivation). Thus, unlike Combes et al. (2019) who model the cost of agglomeration as dependent on population and land area, we have output density $(X_{i,t}/\bar{T}_i = (\sum_\theta L_{i,t}^\theta \varphi_{i,t}^\theta)/\bar{T}_i)$ on the right-hand-side of the structural specification. For comparison, we also estimate the employment density elasticity in Column (2), which takes the value of 0.2. This value is between the average in the literature of 0.15 reported by Ahlfeldt and Pietrostefani (2019) and the predicted value of 0.25 for a country with the urban density of Germany (2,800 residents per km^2, see Demographia (2019)) according to the rule of thumb suggested by the same authors. The value is towards the lower bound of the 0.2-0.27 range reported for France by Combes et al. (2019), which is consistent with France having a higher urban density (3,100 residents per km^2) than Germany. Notice that the estimated density elasticity of housing expenditure $(1-\alpha)\frac{\partial \ln p_{i,t}}{\partial \ln (L_{i,t}/\bar{T})} = 0.066$ substantially exceeds our κ^θ estimates for all groups, implying a unique spatial equilibrium with migration costs unless the density elasticity of amenity ζ^θ is large and positive. Note that our estimate of β implies a housing supply elasticity $(1-\beta)/\beta$ of about 4.2, which is close to existing structural estimates (Epple et al., 2010).

E.6   Regional amenity $(\zeta^\theta, \bar{A}_{i,t}^\theta)$

The structural residual and the estimate of γ^θ from equation (21) together identify the regional amenity $A_j^\theta = \exp\frac{\bar{e}_j^{d\theta} + e_{j,t}^{d,\theta}}{\gamma^\theta}$. The economics behind this identification share similarities with the concept of compensating differentials in the Rosen-Roback framework. If at similar migration costs two destinations obtain similar migration probabilities, but one destination offers a higher real wage, this is rationalized by the other offering greater amenity.

To split the regional amenity into an exogenous and an endogenous component, we use equation (3) and further define the exogenous group-region-year amenity as $\bar{A}_{i,t} = \exp(\tilde{a}_g^{A,\theta} + e_{i,t}^{A,\theta})$, where $\tilde{a}_g^{A,\theta}$ is a group-zone-specific legacy effect from the division period and $e_{i,t}^{A,\theta}$ is a structural residual. Log-linearization yields the following group-specific regression model, which identifies the group-specific density

elasticity of amenity ζ^θ and the exogenous group-region-year amenity $\tilde{A}^\theta_{i,t} = \frac{G_t}{\bar{L}}\bar{A}^\theta_{i,t}$ up to a constant:

$$\ln A^\theta_{i,g,t} = a^{A,\theta}_{g,t} + \zeta^\theta \ln\left(\frac{L_{i,t}}{\bar{T}_i}\right) + e^{A,\theta}_{i,g,t}, \tag{25}$$

where $a^{A,\theta}_{g,t} = \tilde{a}^{A,\theta}_g + \ln\frac{G_t}{\bar{L}}$ collects the effects of public spending and the group-zone-specific exogenous amenity. We once more use the deep lag of population density as an instrument for output density and cluster standard errors on regions. This addresses the reverse causality concern that contemporaneous shocks may affect density through migration.

Our estimates of the density elasticity of the region-group amenity ζ^θ illustrated in Figure 5 vary between about zero and -0.095, revealing that disamenties from density represent an additional congestive force. At a weighted average elasticity of -0.0687, endogenous (dis)amenities in this respect are about as important as housing costs (the estimated density elasticity of housing cost is 0.066). Once more, there is significant heterogeneity across groups, with older skilled workers deriving the largest disutility from density. An econometric analysis of the conditional variation in our ζ^θ estimates across groups is in Column (4) of Table 1.

E.7   Summary

To summarize our identification strategy, we calibrate parameters $\{\alpha, \rho\}$ and identify γ^θ from (20) and (21), κ^θ from (23), β from (24), and ζ^θ from (25) using observed values of the endogenous variables $\{L^\theta_{i,t}, X_{i,t}, w^\theta_{i,t}, p_{i,t}, \chi^\theta_{ij|i,t}\}$. This system of equations is exactly identified. Given the estimated and calibrated parameters together with the observed values of the endogenous variables, we then identify the exogenous variables $B^\theta_{ij,t}$ from (20), $\tau^\theta_{ij,t}$ from (20) and (21), $\psi^\theta_{i,t}$ from (23), $\eta_{i,t}$ from (24), and, up to a constant, $\bar{A}^\theta_{i,t}$ from (20), (21), and (25).

E.8   Overidentification

In this section, we summarize the results of overidentification tests in which we correlate selected exogenous variables with observable measures that were not used in the identification. Full estimation results are in Appendix Section N.1

We estimate a distance elasticity of migration costs of 1.13, which compares to 0.02 for the US and 0.15 for Indonesia (Bryan and Morten, 2019). These sizable differences are in line with Figure 2 which suggest that migration costs steeply increase up to a distance of about 200 km. Germany has less than 20% of the area of Indonesia which has in turn less than 20% of the area of the US. Provided

that the average migration distance in a geographically larger country is greater, the non-linearity of the distance cost implies that the average distance elasticity will be smaller. In line with Bryan and Morten (2019) and Falck et al. (2012), we also find that migration costs are positively correlated with a measure of cultural distance. Conditional on the geographic distance effect, we estimate a cultural distance elasticity of migration cost of 0.15. As novel results, we find that the cultural distance effect on migration cost is about twice as large for men (0.22) than women (0.09), close to and indistinguishable from zero for the high-skilled (0.02), and even negative and significant (-0.05) for workers aged 51-65.

F Solving for the spatial equilibrium

In section C.4, we showed that for given values of parameters and exogenous variables there exists a unique stationary regional employment vector for each group θ such that the spatial equilibrium condition (14) holds. Having identified the required values in Section E, we discuss in this section the numerical procedure to solve for the long-run spatial equilibrium, the associated stationary employment vectors and the matrices that define the transition path to the equilibrium. We then document the model solution for density, wages, housing costs, the share of high-skilled workers, and expected utility across space. Finally, we compare the spatial distribution of selected endogenous outcomes in a spatial equilibrium with and without migration costs.

F.1 Numerical procedure

We start from a spatial economy described by the group-specific parameter values for $\{\alpha, \beta, \rho, \zeta^\theta, \kappa^\theta\}$ and the exogenous variables $\{\psi_{i,t}^\theta, \eta_{i,t}, \bar{A}_{i,t}^\theta, \tau_{ij,t}^\theta, B_{ij,t}^\theta\}$ identified in section E, as well as the set of group-specific vectors of observed regional employment $L_{i,t}^\theta$. Our task is to identify the Θ equilibrium vectors $L_{i,t}^{\theta}{}^*$ that satisfy the stationarity condition (14) for all groups θ. As discussed in C.4, there is a direct mapping from $L_{i,t}^{\theta}{}^*$ to equilibrium values of all other endogenous variables $\{A_{i,t}^{\theta}{}^*, w_{i,t}^{\theta}{}^*, p_{i,t}^{\theta}{}^*, \chi_{ij|i,t}^{\theta}{}^*\}$.

To solve for the stationary employment vector, we use an iterative fixed point procedure that exploits the structure of the model and converges rapidly to a unique equilibrium. In particular, we use the migration gravity equation (11) to predict a matrix of migration probabilities which is then used to forecast a new regional

employment vector that corresponds to the sum of inflows as laid out in (12):

$$L_{i,z+1}^{\theta} = \chi_{ij,z}^{\theta} * L_{i,z}^{\theta}, \tag{26}$$

where $\chi_{ij,z}^{\theta}$ denotes the matrix of conditional migration probabilities at iteration $z = 1, 2, ..., \mathcal{Z}$ and $L_{i,z=1}^{\theta} = L_i^{\theta}$ is our initial guess. We use 2017 values for all variables as starting points. In each iteration, the migration-induced change in employment $\left(L_{i,z+1}^{\theta} - L_{i,z}^{\theta}\right)$ maps to a new employment vector $L_{i,z+1}^{\theta}$, which leads to an update of endogenous amenities, wages, housing costs and migration probabilities $\chi_{ij,z+1}^{\theta}$ according to (3), (5), (7), and (11). We repeat this procedure until iteration $\mathcal{Z}$ when $\left(L_{i,z=\mathcal{Z}+1}^{\theta} - L_{i,z=\mathcal{Z}}^{\theta}\right) = 0$, i.e. all employment vectors are stationary as required by condition (14).

F.2 Spatial distribution of economic activity and utility

In Figure 6, we map the spatial equilibrium values for density, wages, and housing costs and the high-skilled share. In keeping with intuition and the observed values in the data, densities, wages, and housing costs are higher in labour market areas with large core cities (indicated by the coloured circles). The attractiveness of the agglomerated areas in the model can arise from either exogenous productivity, amenity, or housing TFP, or from lower in-migration costs if rebuilding social capital is easier in big cities. The equilibrium share of high-skilled workers also tends to be high in labour market regions with large cities such as Berlin, Munich, or Frankfurt. Within the structure of the model, density-based sorting can arise because parameters determining productivity and amenity effects are gender-age-skill group specific, but housing market parameters are not. Hence, all groups compete on the same regional housing markets and, thus, face similar housing-supply-driven costs of agglomeration. This leads to sorting of those groups into denser regions who experience greater benefits from agglomeration. The elevated share of high-skilled workers in urbanized regions is consistent with the relatively large returns to agglomeration of this group (see Table 1). We note that we generally find a positive but imperfect correlation between spatial equilibrium values and observed values for endogenous variables (see appendix section O).

Figure 7 maps the spatial variation in expected utility as defined in (13). The main takeaway of the upper panels is that in a spatial equilibrium with migration costs, utility is not equalized across locations. Utility differs across regions in a way that it differs by group. As an example, expected utility tends to be large in the agglomerated areas for the unskilled workers, whereas it tends to be lower in the

agglomerated areas for skilled workers owing to a greater disutility from density (see Figure 5). In the bottom panels, we break down the expected utility $\mathcal{U}$ into the regional utility component $\mathcal{V}$ and the migration option value $\mathcal{O}$ defined in (13). As illustrated examplarily for the high-skilled, both components of regional utility are not necessarily closely correlated in space. To shed light on the relative importance of the migration option value, we regress the group-region log of $\mathcal{U}$ against the log of $\mathcal{V}$ and the log of $\mathcal{O}$ in Table 3, controlling for group effects. Across groups, the elasticity of expected utility with respect to the migration option value is about 0.17. The elasticity of expected utility with respect to regional utility is larger, on average (0.35), and there is more variation. In relative terms, the option value of accessing a range of destinations through migration at low cost is most important for the high-skilled.

F.3   Spatial equilibria with and without migration costs

Our model features a spatial equilibrium without migration costs as a special case. To evaluate the effect of migration costs on the equilibrium distribution of economic activity, we solve for the spatial equilibrium without migration costs using the procedure outlined in F.1, setting $\tau_{ij}^{\theta} = 0$. Note that because there is an isomorphic model formulation in which amenity shocks are shocks to migration costs, we set $B_{ij,t}^{\theta} = 1$ in the no-migration-costs scenario. Figure 8 maps the ratio of the values solved for the spatial equilibrium with migration costs (illustrated in Figure 6) over the respective values in the spatial equilibrium without migration cost. The striking insight is that migration costs lead to significantly greater concentration of workers in agglomerated labour markets (with large cities indicated by circles), potentially reflecting that the costs of migrating into agglomerations is lower, e.g. because social capital is easier to accumulate. To substantiate this interpretation, we estimate the density elasticity of in-migration costs. To this end, we regress bilateral migration costs $\tau_{ij,t}^{\theta}$ recovered from (20) and (21) against 10-km distance bin effects, origin-group effects and destination-group effects. We then recover the latter and regress them against the log of regional density and present the results in in Table 4. The estimated elasticity ranges from -0.16 for the unskilled to -0.22 for the high-skilled, with an average across all groups of -0.2. Density-biased migration costs, hence, represent an agglomeration force that has been overlooked in a sizable literature on the economic effects of density summarized by Ahlfeldt and Pietrostefani (2019). It may help rationalizing high and increasing levels of urbanization despite agglomeration elasticities of wages and urban costs that tend to be within the same range Combes et al. (2019).

Comparing the spatial equilibria with and without migration costs, we illustrate some general equilibrium effects that arise from the presence of migration costs in Table 5. Migration costs increase the weighted average density by almost 80%. Because of the associated productivity gains, output as well as wages are 6% higher. Per-m^2 housing costs increase by 69% for the unskilled to about 107% for the high-skilled who tend to live in the most agglomerated areas. As a result, housing consumption decreases by 26% (unskilled) to 40% (high-skilled) which corresponds to more than 10 square meters per worker in absolute terms.

G   Evaluating the effects of spatial shocks

In this section, we discuss how the model can be used to evaluate the aggregate and distributional effects of spatial shocks in the presence of migration costs. We start from the spatial equilibrium introduced in F, denoted by $*$ and introduce a counterfactual equilibrium denoted by c to which the spatial economy transitions following a shock modelled as a change in an exogenous variable. The predicted relative changes in the endogenous variables such as labor allocation, wages, housing prices, amenities, and welfare can be interpreted as the causal effect of a spatial shock in general equilibrium.[13] This approach is very flexible and applicable to any spatial shock or policy that can be expressed as a change in exogenous productivity, amenity or housing TFP (we provide three illustrative applications in Section H).

G.1   Solving for the counterfactual equilibrium

Starting from the values for the parameters and exogenous variables identified in Section E, we model a spatial shock as the change in one or more exogenous variables. Using the counterfactual values of exogenous variables, we then apply the iterative fixed point procedure laid out in Section F.1 to solve for the counterfactual employment vector that maps to all other endogenous variables as explained in C.4. Since there is a unique solution for given values of parameters and exogenous variables, we can identify the counterfactual equilibrium using arbitrary initial guesses for the employment allocation, in principle. However, to identify the transition matrix $\mathcal{M}_{ij}^{\theta}$ that governs the transition from the spatial equilibrium employment allocation to the counterfactual equilibrium employment allocation, it is critical to use the spatial equilibrium employment vector $L_i^{\theta *}$ as starting values. We show how to use the transition matrix to pin down welfare effects in the presence of migration costs in

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[13]See the appendix for a more detailed description of this procedure.

the next subsection.

G.2 Counterfactual effects on worker group welfare

To compute the welfare effects of spatial shocks, we account for the migration responses of workers and the associated migration costs. Intuitively, the effect of a spatial shock on the utility of a worker is determined by the expected utility at a worker's location i in the original spatial equilibrium, $\mathcal{U}_i^{\theta*}$, the expected utility in the counterfactual spatial equilibrium at the location j a worker chooses to migrate to in response to the spatial shock, $\mathcal{U}_j^{\theta c}$, and migration costs associated with the move from i to j:

$$\widehat{\mathcal{U}_{ij}^{\theta}} = \frac{\mathcal{U}_j^{\theta c}}{\mathcal{U}_i^{\theta*}} \frac{m_{ij}^{\theta}}{m_{ii}^{\theta}}. \tag{27}$$

As migration costs only occur at the end of the migration period, we multiply the ratio of utilities by $m_{ij}^{\theta}/m_{ii}^{\theta}$. The average group-region effect measured at the origin is then simply the weighted average of the relative utility changes across all destinations:

$$\widehat{\mathcal{U}_i^{\theta}} = \frac{1}{L_i^{\theta*}} \sum_j \mathcal{M}_{ij}^{\theta} \widehat{\mathcal{U}_{ij}^{\theta}}, \tag{28}$$

where the transition matrix $\mathcal{M}_{ij}^{\theta} = max\left\{\sum_{z=1}^{\mathcal{Z}} \left(M_{ij,z}^{\theta} - M_{ji,z}^{\theta}\right); 0\right\}$ summarizes the positive net migration flows between locations. Notice that we compute $\mathcal{M}_{ij}^{\theta}$ as the sum over all iterations $\mathcal{Z}$ in the solution algorithm. Positive net-outflows are mirrored by negative net-inflows, mechanically. These negative net-inflows receive zero weights since they are redundant in the calculation of $\widehat{\mathcal{U}_i^{\theta}}$ as we track workers from migration origins to destinations. Hence, equation (28) describes the average welfare change of all individuals from group θ who lived in i before the shock.

This transition matrix also enables us to compute the group-specific shares of workers per origin region i whose utility has increased as $\lambda_i^{\theta} = \left(\sum_j \mathcal{M}_{ij}^{\theta} I(\widehat{\mathcal{U}_{ij}^{\theta}} > 0)\right)/L_i^{\theta*}$, where $I(.)$ is an indicator function returning a value of one if the condition is true, and zero otherwise. Note that positive spatial shocks can lead to negative effects on region-groups because immigrants with high wages and low migration costs tend to congest the housing markets at the expense of the most vulnerable groups with high migration costs and low returns to agglomeration.

G.3 Aggregate and distributional effects

Having computed the group-region-specific counterfactual effects on utility, the last step in the evaluation of the welfare effects of a spatial shock consists of the aggre-

gation of group-region utilities. To this end, we define a social welfare function in the tradition of Atkinson (1970) as

$$\mathcal{W}(\varepsilon) = \frac{1}{1-\varepsilon} \sum_i \sum_\theta \left(\mathcal{U}_i^\theta \right)^{1-\varepsilon} \frac{L_i^\theta}{\bar{L}} = \mathcal{U} \left(1 - \mathcal{I}(\varepsilon) \right), \tag{29}$$

where $\mathcal{U}$ is the weighted average of individual utility (including migration costs) and $\mathcal{I} \in [0,1]$ represents the Atkinson measure of inequality (see Appendix K.4 for derivation details). This formulation separates social welfare into a scale-dependent part (average utility) that enters positively into social welfare and a scale-independent inequality measure that imposes a penalty on inequality. The strength of the penalty is governed by the inequality aversion parameter $0 \leq \varepsilon \neq 1$. If $\varepsilon = 0$, $1 - \mathcal{I} = 1$, social welfare is solely determined by the aggregate (utilitarian case). The inequality penalty increases in ε, with $\varepsilon \to \infty$ representing the limiting Rawlsian case in which the penalty is entirely determined by the weakest region-group. To build intuition, we highlight two further values of ε which we use in the applications in Section H. At $\varepsilon = 0.5$, the distribution of region-group utilities in the spatial equilibrium derived in Section F gives $\mathcal{I} = 0.68$, which implies that about two thirds of the aggregate utility in the economy would suffice to deliver the same level of social welfare if it was equally distributed across region-groups. At $\varepsilon = 2$, the *equally distributed equivalent* drops to about one third. We refer to these critical values as representing weak and strong inequality aversion. For the interested reader, we provide a deeper discussion of the effect of ε on the inequality penalty, distinguishing between different inter-region and inter-group inequality as well as expected utility and income as welfare measures in Appendix K.4.

We compute $\mathcal{W}$ for both the baseline ($*$) and the counterfactual (c) spatial equilibrium. While $\mathcal{U}_i^{\theta*}$ is simply the expected utility given by equation (13), the counterfactual group-region utility measured at the migration origin depends on the expected utility in the counterfactual equilibrium at the destination and the migration costs associated with spatial moves caused by a shock. Using the "exact hat algebra" approach by Dekle et al. (2007) and equations (28) and (27), we get $\mathcal{U}_i^{\theta c} = \widehat{\mathcal{U}_i^\theta} \mathcal{U}_i^{\theta*}$. We are then ready to obtain the change in social welfare in the counterfactual spatial equilibrium for a given level of inequality aversion as

$$\widehat{\mathcal{W}}(\varepsilon) = \frac{\mathcal{U}^c}{\mathcal{U}^*} \frac{1 - \mathcal{I}(\varepsilon)^c}{1 - \mathcal{I}(\varepsilon)^*}. \tag{30}$$

With this formulation, we acknowledge the efficiency-equity trade-off that is inherent to many spatial shocks and policies. If there is a positive effect on aggregate

welfare accompanied by an increase in inequality, the effect on social welfare qualitatively and quantitatively depends on inequality aversion.

H   Applications

To illustrate the model's potential, this section uses the procedure outlined in G to evaluate the aggregate and distributional consequences of three spatial shocks that affect one of the three key exogenous variables in the model: 1) trade shocks, modelled as a change in exogenous regional productivity; 2) change in land use regulations, modelled as a change in exogenous housing supply; 3) regional transfers, modelled as an exogenous change in publicly provided local amenities.

We derive relative changes in various endogenous outcomes as well as for social welfare under no ($\varepsilon = 0$), moderate ($\varepsilon = 0.5$) and strong ($\varepsilon = 2$) inequality aversion. We conduct all counterfactuals for a scenario with and without migration costs. Because there is an isomorphic formulation in which bilateral amenity shocks $B_{ij,t}^{\theta}$ correspond to shocks to migration costs, we abstract from the latter in the no-migration-cost scenarios.

We express all results of the counterfactual analyses as changes relative to the spatial equilibrium identified in section F. To keep the presentation compact, we present one table only per counterfactual. We discuss some spatial pattern of the considered shocks and their effects in the text. For the interested reader, the distributions we refer to are mapped in Appendix P along with further detail on the construction of the shock measure where appropriate.

H.1   Trade shocks

Increasing exposure to international trade has been shown to have spatially variant effects on local labour markets (Autor et al., 2013; Dauth et al., 2014). In this section, we evaluate the general equilibrium effects of the exposure of German labour market regions to increasing trade with Eastern Europe and China.

Dauth et al. (2014) provide reduced-form estimates of the effects of the sharp increase in trade with China and Eastern Europe experienced over the 1998-2008 period on various labour market outcomes. Because they use a different definition of local labour markets, we first reconstruct their import and export exposure measures for our geographies as described in Section D and then regress the 1998 to 2008 log change in exogenous productivity $\psi_{i,t}^{\theta}$ obtained from equation (23) against a full set of exposure (import and export)-group (18 group dummies) interactions,

controlling for mean reversion via the 1998 level in exogenous productivity. As discussed in more detail in Appendix P.1, we then take the values predicted by the trade exposure interactions as a region-group-specific measure of the trade-induced shock to exogenous productivity. We note that this shock favours middle-skilled and high-skilled middle-aged male workers and, moderately, western regions.

The results of the counterfactual analysis are in Table 6. Output increases, overall, and in particular in the west, owing to migration from the east to the west. This migration is driven by the density bias in migration costs and the fact that western regions are denser, on average. The shock itself favours western regions only marginally and is not density biased. The increase in the employment-weighted average density leads to higher housing costs and lower housing consumption. As a result, the effect on unweighted welfare (for $\varepsilon = 0$) is marginal, despite increases in wages. The shock is skill-biased, favouring middle-skilled and high-skilled workers, and it leads to an increase in spatial inequality. Therefore, social welfare decreases already with moderate inequality aversion ($\varepsilon = 0.5$). While the majority of workers benefits from the positive shock, a significant fraction of workers lose. These include 28% of the high-skilled, owing to increasing congestion on housing markets. Reflecting the skill bias in the shock, the share is significantly higher for the unskilled. Given that the shock had, on average, similar effects in the west and in the east, it is no surprise that the share of winning workers is roughly comparable in both regions.

Setting migration costs to zero, migration is less directed towards dense areas in the west and the average density does not increase, implying that housing costs and consumption do not change much. The skill bias in the shock is reflected in a lower share of winning workers among unskilled workers, but the effects are generally similar across the east and the west. While the high-skilled gain, on average, subgroups (e.g. old female workers) still lose. Since utility is equalized in space, there is little effect on spatial inequality so that the choice of inequality aversion (governed by ϵ) matters less for social welfare.

H.2   Land use regulation

Restricted supply of housing due to land use regulations are often blamed for reducing housing affordability and economic welfare (Glaeser et al., 2005). In this section, we evaluate the general equilibrium effects of relaxing housing supply constraints in the more constrained western regions so that the average housing TFP matches the level of the more productive eastern regions.

During the division period, former East Germany was governed by a socialist

planning regime with an emphasis on the provision of affordable housing. The relatively large quantities of housing provided came at the expense of poor housing quality. Following Germany's unification, very favourable tax reliefs to real estate investors led to a construction boom and a rejuvenation of the housing stock (Flockton, 1998). Thus, it is no surprise that exogenous housing productivity η_i identified in Section E is 26.6% higher, on average, in eastern than in western regions. Our policy counterfactual is a change in land use regulations in the western regions that brings the average housing productivity to the level of the eastern regions. Therefore, we increase η_i for all West German regions by 26.6%.

The results of the counterfactual analysis are in Table 7. The exogenous change in housing productivity mechanically favours western regions, rationalizing migration from the east to the west. Migration occurs primarily into denser regions, in particular in the scenario with migration costs, owing to the density-bias in migration costs. Total output and wages, thus, increase due to agglomeration economies. As expected, the increase in housing productivity in the west leads to reduced housing rents, greater housing consumption and, thus, an increase in aggregate welfare that exceeds wage growth. In the scenario with migration costs, social welfare increases less if $\varepsilon > 0$, reflecting regressive distributional effects. While the great majority of the population benefits from the increase in housing productivity, slightly less than 10% are net losers. In contrast, with perfect spatial arbitrage there is, mechanically, no increase in inequality in welfare so that everybody benefits, once more highlighting the limitations of a conventional spatial equilibrium framework for the evaluation of distributional effects.

H.3 Regional transfers

Fiscal equalization via regional transfer schemes is an intentional feature of many tax systems. Yet, regional transfers are often criticized on grounds of being inefficient due to distortionary effects on the spatial allocation of resources (Fajgelbaum et al., 2019) and ineffective due to capitalization effects in house prices (Kline and Moretti, 2014). In this section, we evaluate the general equilibrium effects of a regional transfer scheme similar to the *Solidaritätszuschlag* which was implemented in the aftermath of Germany's unification to support eastern regions at the expense of a higher income tax.

To facilitate this policy experiment, we allow for regional variation in per-capita public spending introduced in equation (3) as follows: $G_i/L_i = (G/\bar{L}) + I(East = 1) * transfer$, where $G/\bar{L}$ is government expenditure net of the costs of the regional *transfer* as determined by the baseline tax rate $\iota = 0.49$ and the government budget

constraint. $I(East = 1)$ indicates eastern regions. Up to this point, this policy experiment is isomorphic to an increase in exogenous amenities $\bar{A}_i$ in the east. To finance the $transfer$, we increase the income tax rate by two percentage points. In relative terms, this is roughly in line with the 5.5%-increment on the income tax that constitutes the *Solidaritätszuschlag*. The government budget constraint then determines the uniform per-capita and year $transfer$.

The results of the counterfactual analysis are in Table 8. In equilibrium, we obtain a sizable per-capita and year increase in public spending in the east of €2,983 in the scenario with migration costs and €2,543 in the scenario without migration costs. This is roughly within the range of the €15.5bn per year volume of the *Solidaritätszuschlag* (excluding €1.8bn collected via an increment on capital gains taxes) spread over about six million workers in the east. Not surprisingly, the transfer scheme leads to migration from the west to the east and a corresponding shift in output. The migration origins tend to be primarily low-density regions in the west given that the average density in the west does not decrease despite the population outflow. The increase in housing demand in the east leads to increasing housing costs and decreasing housing consumption, from which the unskilled suffer more than the skilled groups. This is in line with a large literature on tax-related property price capitalization effects in the tradition of Oates (1969). The increase in density also leads to an increase in average housing costs in the west, despite reduced demand due to the higher income tax. Increased housing costs coupled with reduced demand lead to lower housing consumption.

The perhaps most important insights originate from the analysis of worker welfare. With migration costs, regional transfers lead to an increase in worker welfare in the targeted eastern regions, an effect that is ruled out by assumption in the no migration costs scenario. Yet, despite the decrease in the welfare gap between the west and the east, inequality in the economy as a whole increases so that the social welfare effect becomes more negative as ε increases. This is because those who are already economically advantaged, respond stronger to the change in economic incentives when making location decisions. In relative terms, the high-skilled respond significantly stronger by migrating from the west to the east than the other skill groups. Another interesting insight is that the transfer produces losers in the positively targeted regions in the east, and winners in the net-contributing west. This is because the amenity increase in the east attracts mobile workers from the west, who then congest housing markets in the east, reducing welfare of the most vulnerable immobile groups. Reflecting greater mobility, the share of winners in the west is greatest among the high-skilled. In the no migration costs scenario, the moder-

ate decrease in welfare, owing to the distorted allocation of resources, mechanically translates into a decrease in welfare for all workers.

I Conclusion

We develop a quantitative spatial model with heterogeneous workers and migration costs. Within our theoretical framework, we can solve for the long-run spatial equilibrium to which an economy would converge in the absence of further shocks to exogenous productivity, housing TFP and amenity. This novel feature facilitates equilibrium-to-equilibrium counterfactual analysis of the causal effects of spatial shocks in a general spatial equilibrium with migration costs. In contrast to standard spatial equilibrium frameworks which assume perfect mobility, our model accounts for distributional consequences of shocks with spatially variant effects that interact with migration costs.

To illustrate the policy implications, we show how to use our framework for the counterfactual analysis of general equilibrium effects of spatial shocks in the presence of migration costs as well as how to represent social welfare in a spatial economy with inter-group and inter-region inequality for varying levels of inequality aversion. We then provide three applications to illustrate the model's potential, but the framework we present is very flexible and can be used for the evaluation of any shock or policy that affects regional productivity, housing TFP or amenity. Highlighting the fundamental implications of incorporating migration costs into the evaluation of spatial phenomena, the results of the three applications challenge conventional wisdom in spatial economics.

One takeaway is that positive shocks or policies with spatially varying effects do not necessarily lead to Pareto improvements in welfare. While Germany is arguably a net-beneficiary of globalization, trade exposure benefits some regions and worker groups more than others, leading to increasing inequalities and spatial adjustments that are not costless. Those who respond to economic incentives by choosing to migrate face a cost as they leave social capital behind. Moreover, these movers congest housing markets at their migration destinations, leading to losing worker groups among the stayers in winning regions. Even a localized increase in housing productivity, which seems unambiguously positive from a welfare perspective, triggers migration that can be harmful to the most vulnerable groups, namely those with low returns to agglomeration and high migration resistance.

Another takeaway is that, unlike in the conventional spatial equilibrium framework, regional transfers do improve welfare of workers in the targeted regions since

migration costs create a friction that prevents perfect spatial arbitrage. However, regional transfers into economically weaker regions do not necessarily reduce inequality because those who respond strongest to economic incentives in their location choices tend to be those who are already economically advantaged.

By design, our model can be used to evaluate policies that aim at targeting specific groups and regions. Our hope is that our model will be helpful in rationalizing and eventually mitigating increasing resistance to trade liberalization and other policies that are potentially welfare enhancing even though they disadvantage selected groups in selected regions.

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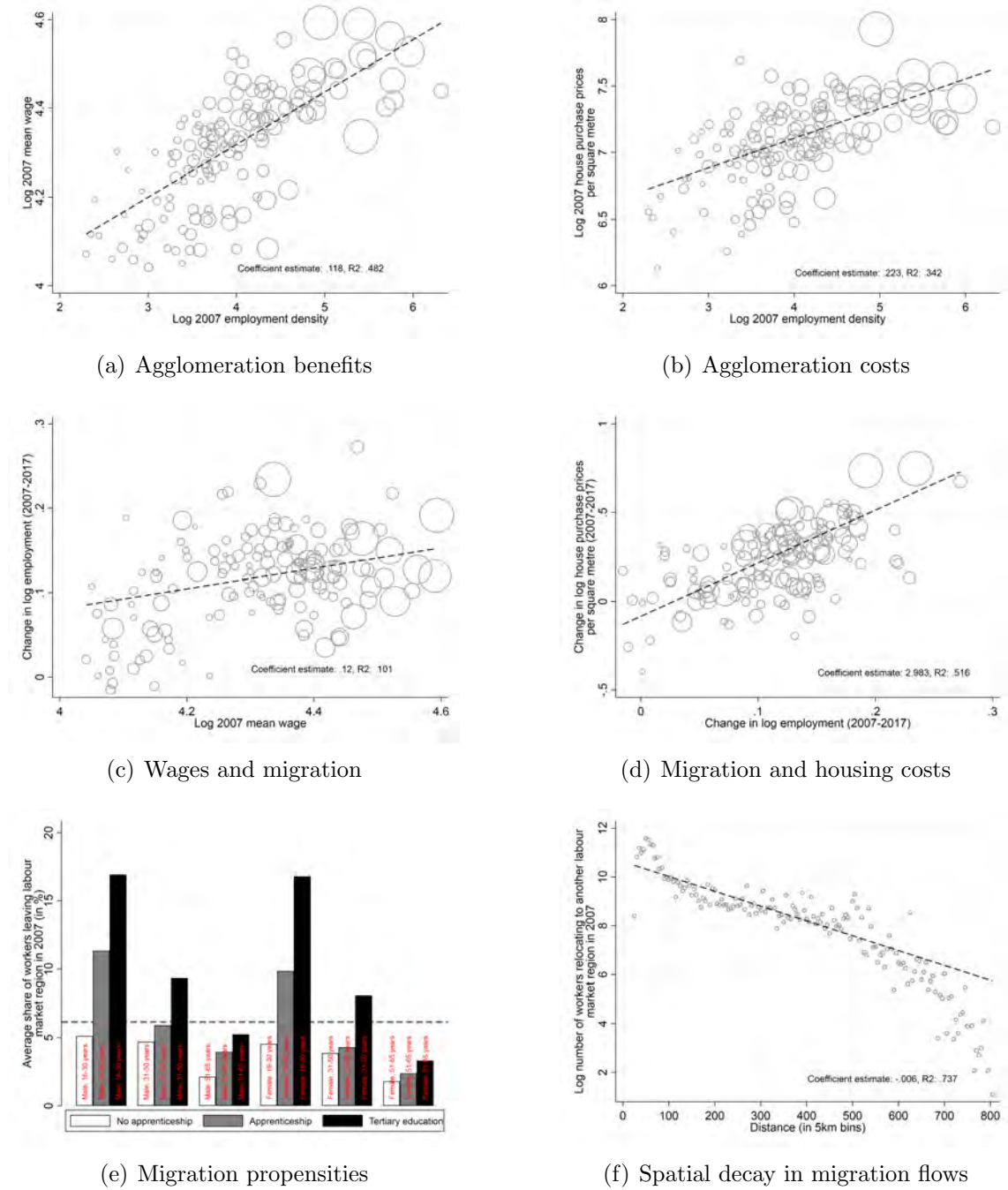**Demographia**, "Demographia World Urban Areas," 2019.

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Figures and Tables
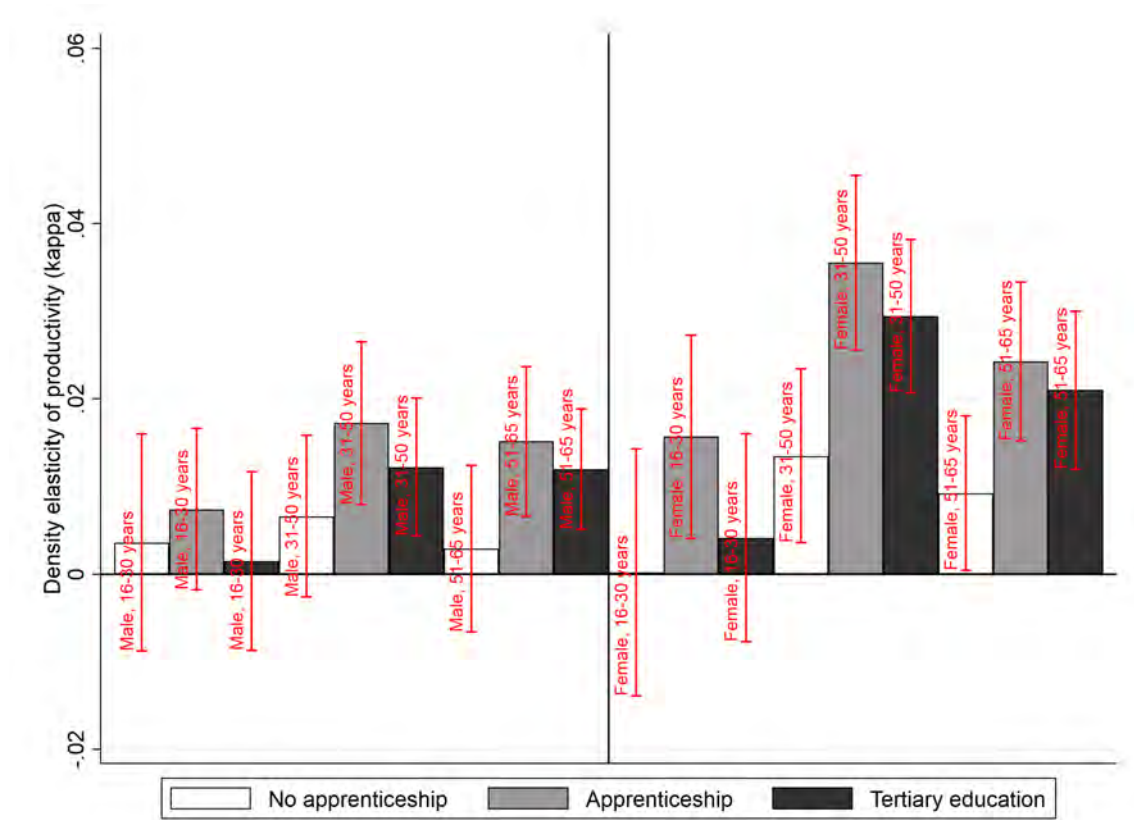
Figure 1: Stylized facts of the spatial economy

(a) Agglomeration benefits

(b) Agglomeration costs

(c) Wages and migration

(d) Migration and housing costs

(e) Migration propensities

(f) Spatial decay in migration flows

Note: Unit of observation is 141 labour market areas as defined by **?**. Wage and employment data based on the universe of full-time workers from the IAB. Housing cost measured as average per-square-meter housing prices.

Figure 2: Migration resistance by group
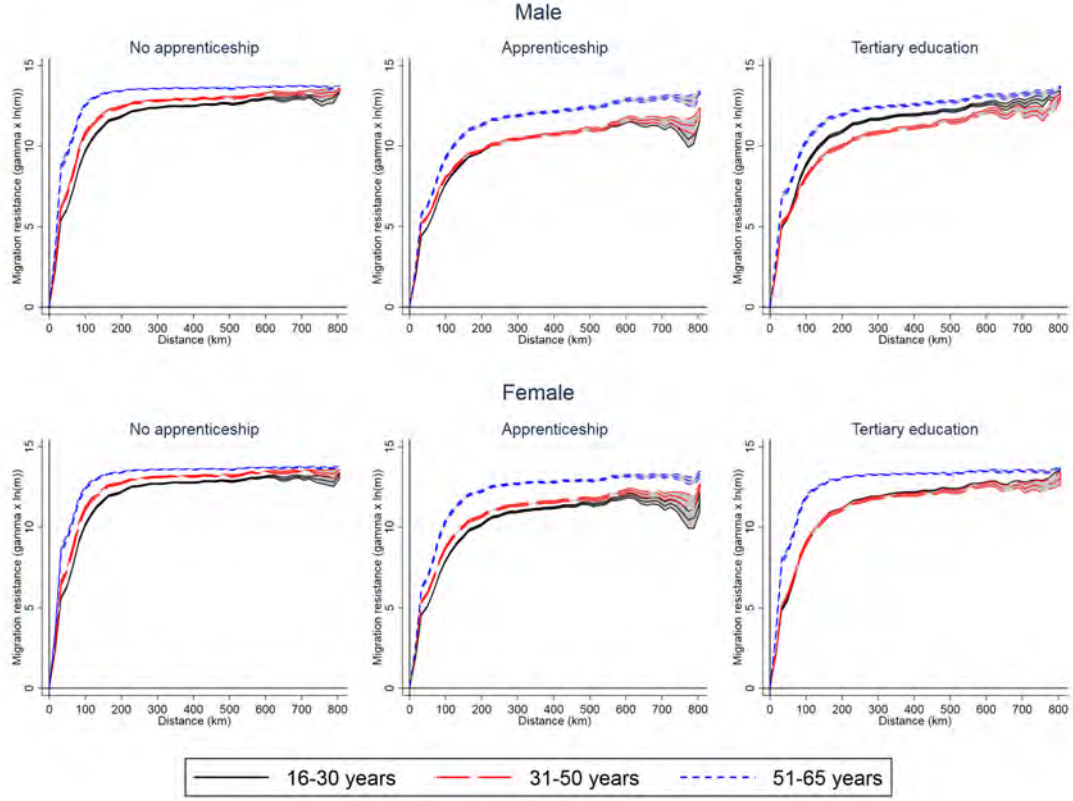
Notes: $\gamma^{\theta} \ln m_{ij}^{\theta} = \tilde{m}_{ij}^{\theta}$ estimates are based on the i-j fixed effect from a regression of the log of bilateral migration shares against origin-year effects, destination-year effects, and origin-destination effects. Point estimates and confidence bands are from locally weighted regressions (Gaussian kernel, bandwidth of 10km).

Figure 3: Density elasticity of productivity

Figure 4: Amenity heterogeneity
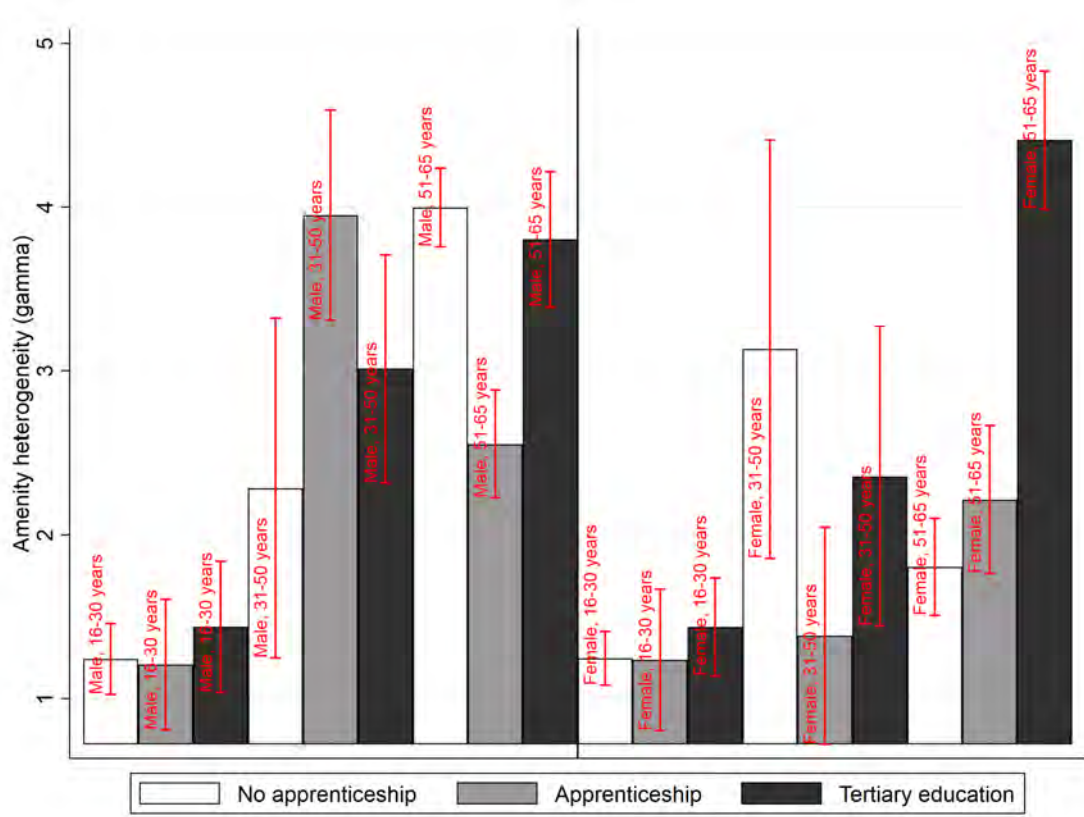
Notes: Estimates from regressions of destination-year effects on the log of real wages, using zone-year interactive dummies as instrumental variables (equation). Destination-year effects from regressions of the log of bilateral migration shares against origin-year effects, destination-year effects and origin-destination effects (equation (21)). Confidence bands are at the 95% level.

Figure 5: Density elasticity of amenity
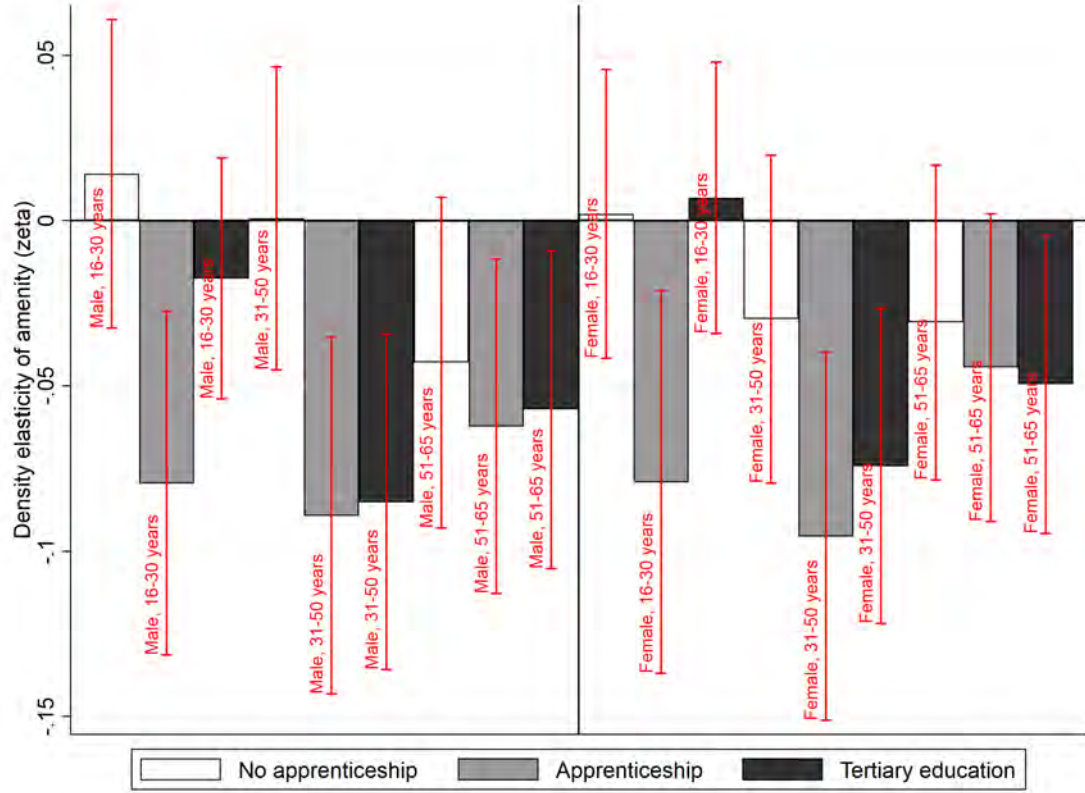
Notes: Elasticity estimates from regressions of region-group amenity against log density, controlling for zone effects (former East vs. former West Germany) and using 1907 log population density as an instrument. Region-group amenity is the adjusted (for amenity heterogeneity) residual from regressions of destination-year effects on the log of real wage - log of housing cost. Destination-year effects from regressions of the log of bilateral migration shares against origin-year effects, destination-year effects and origin-destination effects (equation (25)). Confidence bands are at the 95% level.
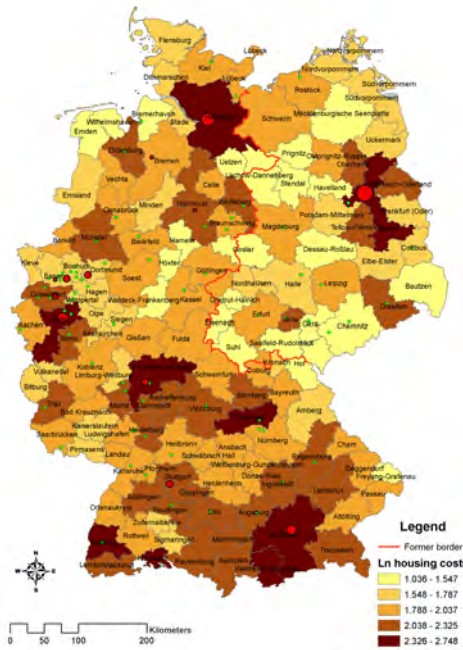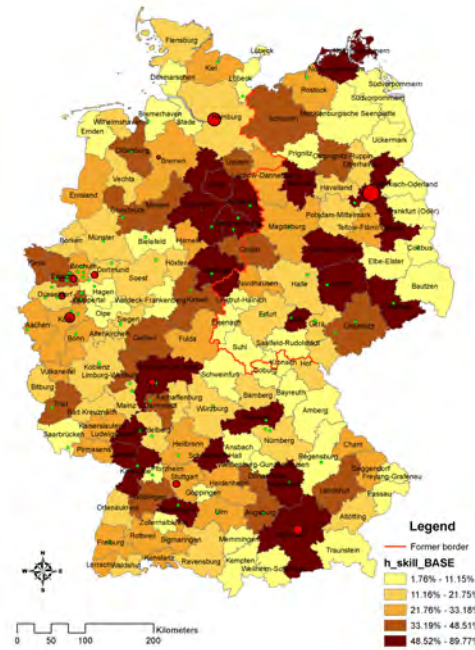
Figure 6: Spatial equilibrium
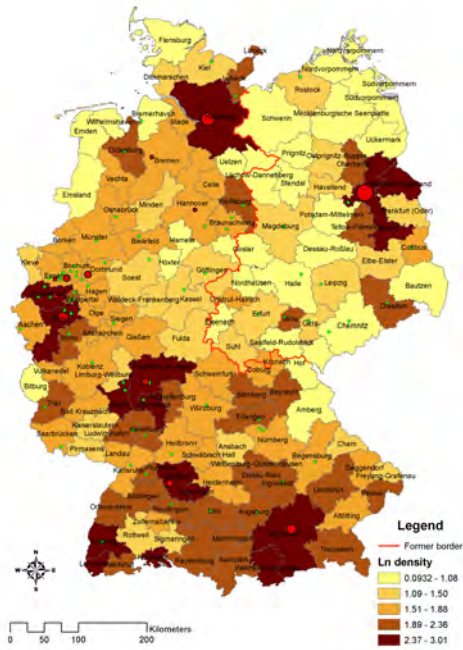
(a) Employment density
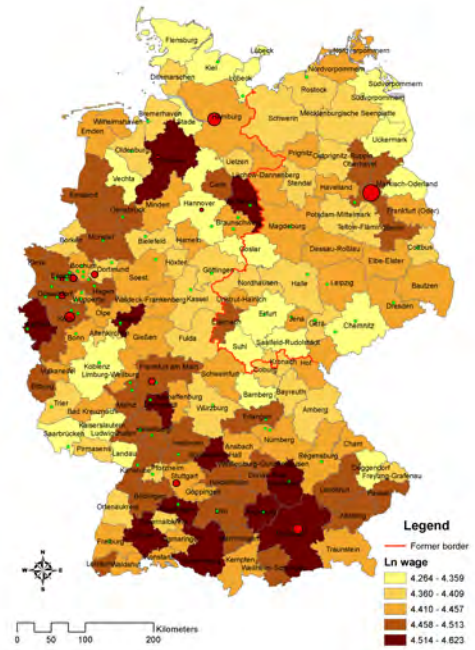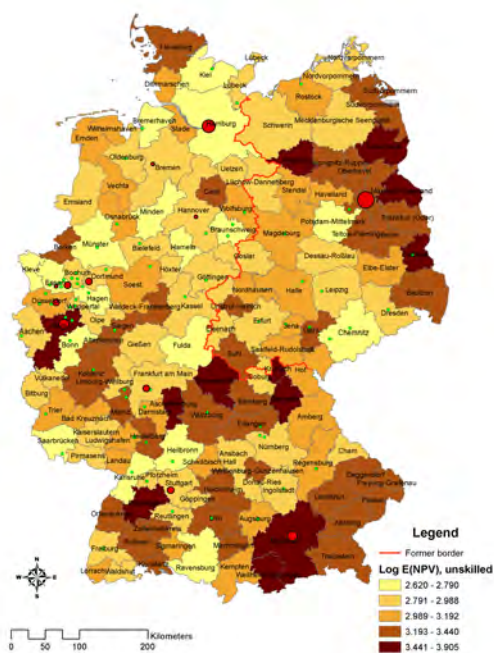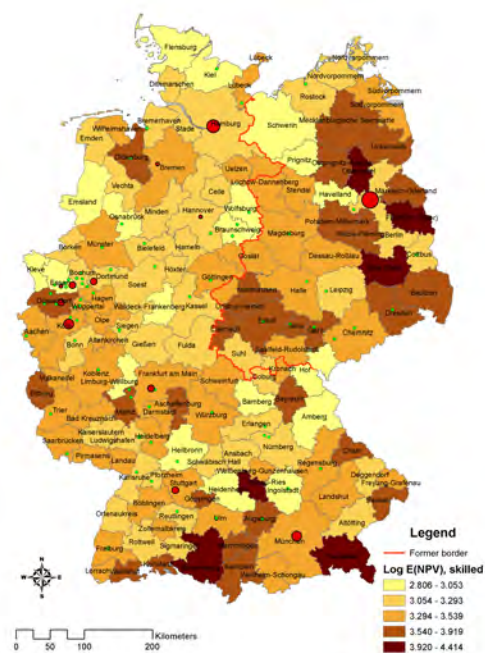
(b) Average wage

(c) Housing cost

(d) Share high-skilled

Note: Predicted values using the structure of the model.

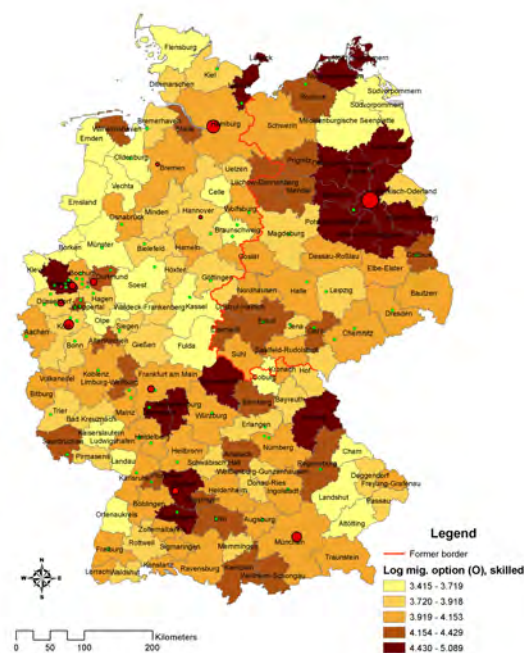Figure 7: Expected utility in spatial equilibrium

(a) Expected utility $\mathcal{U}$, unskilled

(b) Expected utility $\mathcal{U}$, skilled

(c) Regional utility $\mathcal{V}$, high-skilled

(d) Migration option value $\mathcal{O}$, high-skilled

Note: Predicted values using the structure of the model.

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Figure 8: Impact of migration cost on the spatial economy

(a) Employment density

(b) Average wage
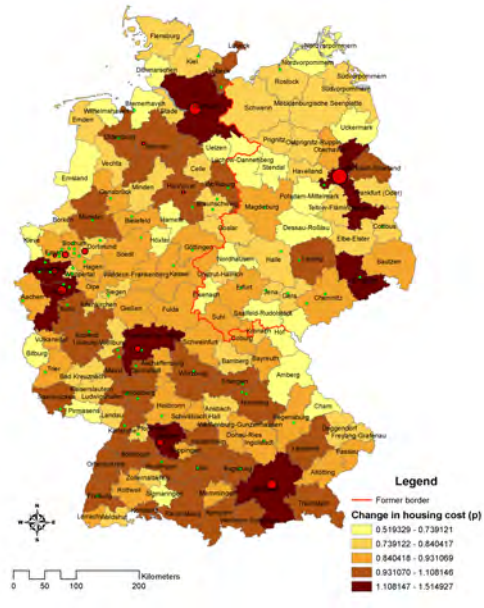
(c) Housing cost
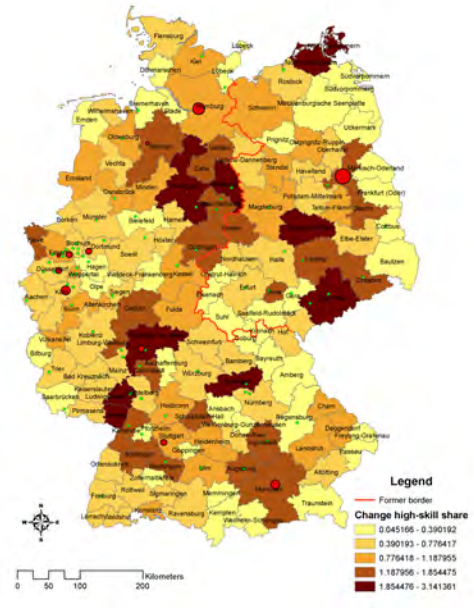
(d) Share high-skilled

Note: Predicted values using the structure of the model. Illustrated changes are defined as the ratio of the values in the spatial equilibrium with migration costs over the spatial equilibrium without migration costs. The latter is solved using the same procedure as the former, with the only difference being that migration costs are set to $\tau_{ij}^{\theta} = 0$.

Table 1: Relative migration resistance by group

	(1) Migration resistance ($\tau\gamma$)	(2) Amenity heterogeneity (γ)	(3) Migration costs (τ)	(4) Agglomeration elasticity (κ)	(5) Amenity elasticity (ζ)
Female	0.499*** (0.00)	-0.474 (0.37)	1.174*** (0.00)	0.008*** (0.00)	0.003 (0.01)
31-50 years	0.121*** (0.00)	1.386*** (0.45)	-3.913*** (0.01)	0.014*** (0.00)	-0.037** (0.01)
51-65 years	1.354*** (0.00)	1.829*** (0.45)	-4.140*** (0.01)	0.009*** (0.00)	-0.022$^+$ (0.01)
Apprenticeship	-1.739*** (0.00)	-0.193 (0.45)	-0.378*** (0.01)	0.013*** (0.00)	-0.061*** (0.01)
Tertiary education	-1.054*** (0.00)	0.458 (0.45)	-1.558*** (0.01)	0.007** (0.00)	-0.032** (0.01)
Constant	11.806*** (0.00)	1.450*** (0.45)	8.642*** (0.01)	-0.006* (0.00)	0.004 (0.01)
Origin-destination effects	Yes	-	Yes	-	-
N	357858	18	357858	18	18
r2	.881	.644	.774	.852	.705

Notes: Unit of observation is origin-destination-group in (1) and (3) and group in (2). Migration resistance is the origin-destination fixed effect from a regression of the log of bilateral migration shares against origin-year effects, destination-year effects, and origin-destination effects. Amenity heterogeneity is from a regression of destination fixed effects against log regional wage normalized by regional housing costs controlling for region effects. Productivity is from group-specific regressions of AKM-adjusted log wages against log employment density and zone (former East vs. West Berlin) using log population density as an instrument. All explanatory variables are binary indicator variables. Standard errors in parentheses.

$^+$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Output density elasticity of housing cost

	(1) Log housing costs (region-year-specific)	(2) Log housing costs (region-year-specific)
Log output density (β)	0.184*** (0.07)	
Log employment density		0.196** (0.08)
Zone effects	Yes	Yes
r2	.321	.301
N	1,551	1,551

Notes: Units of observation are labour market region-year cells. *Housing costs* is the annualized house price index inferred from micro data as described in the data section D.5. We use the 1907 log population density as an instrument for log of output density. Zone effects distinguish between former East and West Germany. Standard errors in parentheses clustered on labour market areas.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Expected utility vs. regional utility and migration option value

	(1) Ln expected utility	(2) Ln expected utility	(3) Ln expected utility	(4) Ln expected utility
Ln Regional utility, spatial eq. with mig. costs	0.346*** (0.00)	0.359*** (0.01)	0.420*** (0.01)	0.260*** (0.01)
Ln Migration option value, spatial eq. with mig. costs	0.168*** (0.01)	0.163*** (0.01)	0.175*** (0.02)	0.175*** (0.01)
Group effects	Yes	Yes	Yes	Yes
Groups	All	Unskilled	Skilled	High-skilled
N	2538	846	846	846
r2	.874	.82	.923	.872

Notes: Unit of observation is group-region. All variables solved using the structure of the model. $^{+}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Density elasticity of in-migration cost

	(1) Ln in-migration costs (model based)	(2) Ln in-migration costs (model based)	(3) Ln in-migration costs (model based)	(4) Ln in-migration cost (model based)
Ln destination density (spatial equilibrium)	-0.198*** (0.01)	-0.159*** (0.01)	-0.211*** (0.02)	-0.223*** (0.02)
Group effects	Yes	Yes	Yes	Yes
Groups	All	Unskilled	Skilled	High-skilled
N	2538	846	846	846
r2	.931	.959	.894	.915

Notes: Unit of observation is group-region. Ln in-migration cost is the destination-group effect from a regression of bilateral migration costs τ_{ij}^{θ} against distance bin effects (10km) and destination-group effects. Spatial equilibrium density solved using the structure of the model. Standard errors in parentheses. $^{+}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Spatial equilibria with and without migration costs

| | (1) | (2) | (3) |
Migration costs:	With	Without	With/without
Output in bn. €	1,037	983	1.06
Weighted average density (emp./km^2)	322	179	1.79
Yearly wage (€), unskilled	27,240	25,631	1.06
Yearly wage (€), skilled	26,761	25,654	1.04
Yearly wage (€), high-skilled	34,891	32,962	1.06
Yearly housing cost (€/m^2), unskilled	234	139	1.69
Yearly housing cost (€/m^2), skilled	234	133	1.75
Yearly housing cost (€/m^2), high-skilled	287	138	2.07
Housing consumption (m^2), unskilled	31	41	0.74
Housing consumption (m^2), skilled	29	43	0.68
Housing consumption (m^2), high-skilled	31	52	0.60

Notes: Equilibrium employment, wages, and housing costs determined using the iterative fixed point procedure described in F taking parameters and exogenous variables as given. Housing consumption is implicitly determined by wages and housing costs according to equation (2).

Table 6: Counterfactual effects: Trade shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Migration cost	Yes	Yes	Yes	No	No	No
Regions	All	West	East	All	West	East
Total output	1.02	1.02	1.02	1.03	1.03	1.00
Employment: Unskilled	1.00	0.99	1.04	1.00	1.00	1.00
Employment: Skilled	1.00	1.00	1.00	1.00	1.00	0.99
Employment: High-skilled	1.00	1.00	0.98	1.00	1.01	0.97
Weighted average density	1.02	1.01	1.13	0.99	0.99	0.98
Yearly wage, unskilled	1.02	1.01	1.05	1.01	1.01	1.01
Yearly wage, skilled	1.02	1.03	1.00	1.03	1.03	1.01
Yearly wage, high-skilled	1.03	1.03	1.01	1.04	1.04	1.02
Yearly housing cost (per m^2), unskilled	1.04	1.03	1.10	1.00	1.00	1.00
Yearly housing cost (per m^2), skilled	0.99	0.99	1.05	1.00	1.00	1.00
Yearly housing cost (per m^2), high-skilled	1.00	1.00	1.03	1.00	1.00	1.00
Housing consumption, unskilled	0.96	0.97	0.92	1.01	1.01	1.01
Housing consumption, skilled	1.01	1.02	0.96	1.02	1.02	1.02
Housing consumption, high-skilled	1.03	1.04	0.98	1.03	1.03	1.03
Welfare, epsilon = 0	1.03	1.03	1.03	1.06	1.06	1.06
Welfare, epsilon = 0.5	1.03	1.03	1.02	1.05	1.05	1.05
Welfare, epsilon = 2	0.96	0.97	0.92	1.04	1.04	1.04
Share winners, high-skilled	0.83	0.83	0.85	0.83	0.82	0.89
Share winners, skilled	0.81	0.83	0.62	0.83	0.83	0.83
Share winners, unskilled	0.74	0.73	0.88	0.67	0.66	0.72

Notes: Except for the last three rows, all results are expressed as the ratio of the values in the counterfactual spatial equilibrium after the spatial over the values in the original spatial equilibrium. Housing consumption is implicitly determined by wages and housing costs according to equation (2).

Table 7: Counterfactual effects: Increase in housing TFP in the west

	(1)	(2)	(3)	(4)	(5)	(6)
Migration cost	Yes	Yes	Yes	No	No	No
Regions	All	West	East	All	West	East
Total output	1.00	1.02	0.88	1.00	1.02	0.90
Employment: Unskilled	1.00	1.01	0.95	1.00	1.02	0.90
Employment: Skilled	1.00	1.01	0.91	1.00	1.02	0.91
Employment: high-skilled	1.00	1.03	0.81	1.00	1.02	0.88
Weighted average density	1.05	1.05	1.00	1.02	1.02	0.89
Yearly wage, unskilled	1.01	1.00	1.03	1.00	1.00	1.00
Yearly wage, skilled	1.00	1.00	0.99	1.00	1.00	1.00
Yearly wage, high-skilled	1.00	1.00	0.99	1.00	1.00	1.01
Yearly housing cost (per m^2), unskilled	0.84	0.81	1.08	0.82	0.79	0.98
Yearly housing cost (per m^2), skilled	0.81	0.79	1.03	0.82	0.79	0.98
Yearly housing cost (per m^2), high-skilled	0.83	0.80	1.00	0.82	0.79	0.97
Housing consumption, unskilled	1.17	1.21	0.94	1.20	1.26	1.02
Housing consumption, skilled	1.21	1.26	0.96	1.20	1.26	1.02
Housing consumption, high-skilled	1.21	1.25	0.99	1.21	1.26	1.03
Welfare, epsilon = 0	1.05	1.06	1.00	1.07	1.07	1.07
Welfare, epsilon = 0.5	1.07	1.07	1.00	1.07	1.07	1.07
Welfare, epsilon = 2	1.01	1.01	0.90	1.07	1.07	1.07
Share winners, high-skilled	0.95	0.95	0.95	1.00	1.00	1.00
Share winners, skilled	0.96	0.96	0.97	1.00	1.00	1.00
Share winners, unskilled	0.97	0.97	0.90	1.00	1.00	1.00

Notes: Except for the last three rows, all results are expressed as the ratio of the values in the counterfactual spatial equilibrium after the spatial over the values in the original spatial equilibrium. Housing consumption is implicitly determined by wages and housing costs according to equation (2).

Table 8: Counterfactual effects: Regional transfer to east

|	(1)	(2)	(3)	(4)	(5)	(6)
Migration cost	Yes	Yes	Yes	No	No	No
Regions	All	West	East	All	West	East
Total output	1.00	0.92	1.54	1.00	0.94	1.26
Employment: Unskilled	1.00	0.95	1.37	1.00	0.95	1.25
Employment: Skilled	1.00	0.95	1.39	1.00	0.95	1.24
Employment: Shigh-skilled	1.00	0.86	1.78	1.00	0.93	1.31
Weighted average density	0.99	0.94	1.57	0.97	0.94	1.29
Yearly wage, unskilled	1.00	1.01	0.98	1.00	1.00	1.00
Yearly wage, skilled	0.99	1.00	1.01	1.00	1.00	1.00
Yearly wage, high-skilled	0.99	1.02	1.00	0.99	1.00	0.98
Yearly housing cost (m^2), unskilled	0.99	1.00	1.05	0.98	0.98	1.04
Yearly housing cost (m^2), skilled	0.97	0.98	1.10	0.98	0.98	1.04
Yearly housing cost (m^2), high-skilled	0.95	0.97	1.06	0.98	0.98	1.05
Housing consumption, unskilled	0.95	0.96	0.86	0.98	0.98	0.92
Housing consumption, skilled	0.97	0.97	0.88	0.98	0.98	0.93
Housing consumption, high-skilled	0.99	1.01	0.89	0.98	0.98	0.90
Welfare, epsilon = 0	0.98	0.96	1.12	0.99	0.99	0.99
Welfare, epsilon = 0.5	0.97	0.97	1.13	0.99	0.99	0.99
Welfare, epsilon = 2	0.91	0.91	1.03	0.99	0.99	0.99
Share winners, high-skilled	0.14	0.08	0.96	0.00	0.00	0.00
Share winners, skilled	0.11	0.01	0.98	0.00	0.00	0.00
Share winners, unskilled	0.12	0.06	0.97	0.00	0.00	0.00

Notes: The regional transfer originates from a 2-percentage point increase in income tax, which is used to finance additional local public services in eastern regions exclusively. Except for the last three rows, all results are expressed as the ratio of the values in the counterfactual spatial equilibrium after the spatial over the values in the original spatial equilibrium. Housing consumption is implicitly determined by wages and housing costs according to equation (2).

ONLINE APPENDIX

This section presents an online appendix containing complementary material.

J   Stylized facts

Figure A1: Migration decay in geographic distance by group
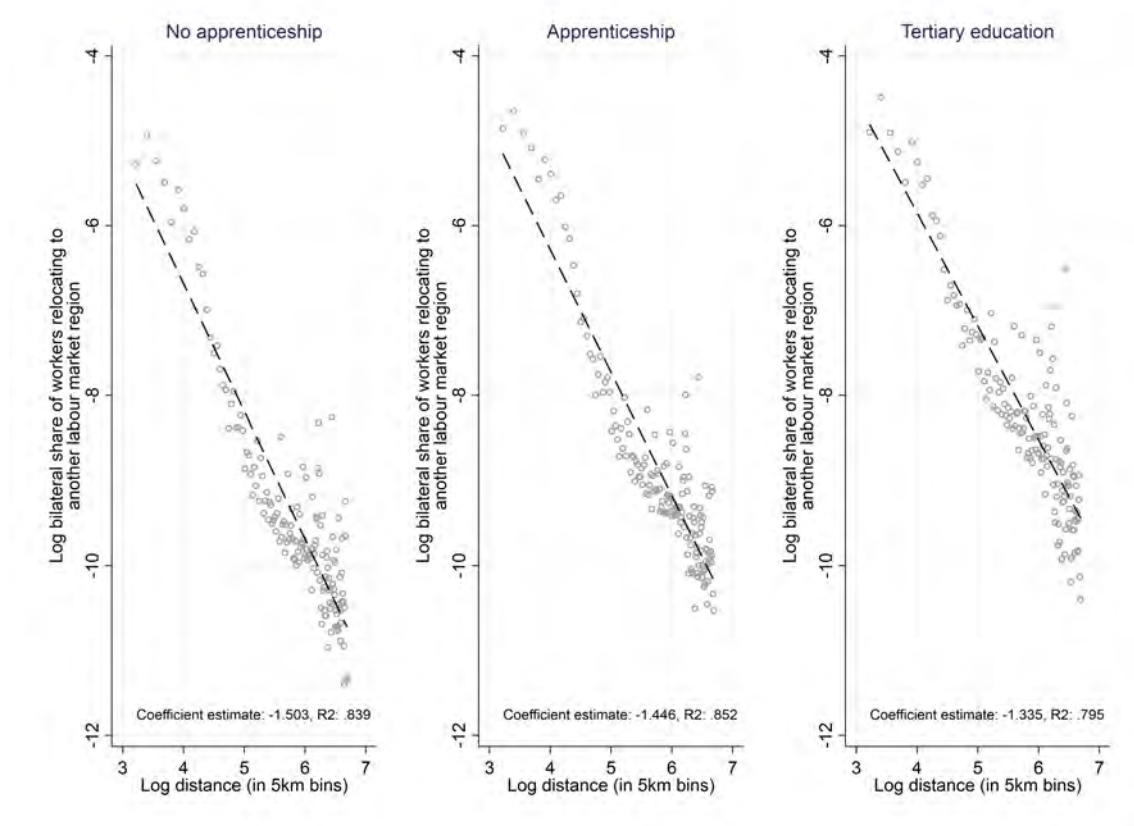
Notes: The figure shows the weighted log share of workers changing their place of employment (relative to employment at the origin region) within log 5 kilometre distance bins for each of the three skill groups. Weights are the employment levels in the origin region.

Figure A2: Migration decay in cultural distance conditional in geographic distance
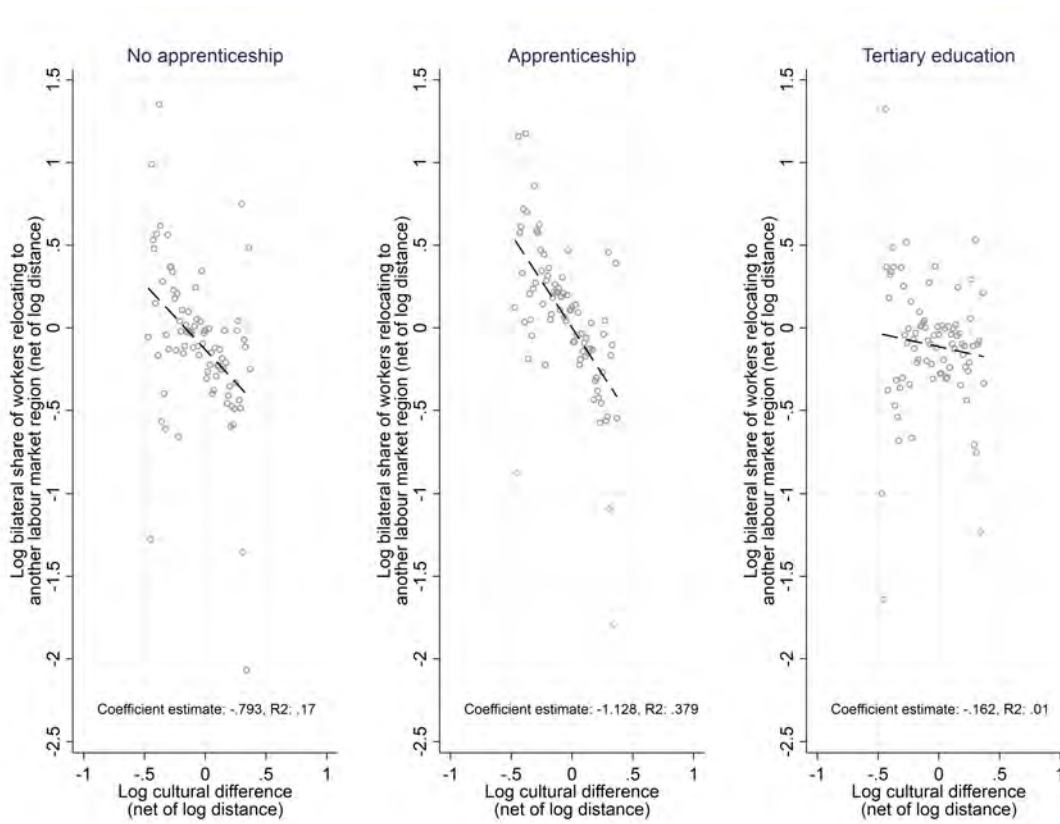
Notes: The figure shows the residual log share of workers changing their place of employment (relative to the employment at the origin region) within 0.01 residual log cultural distance bins. The residual log shares are constructed by regressing the weighted log share of workers changing their place of employment on log distance. Residual log cultural distance is constructed by regressing the weighted log cultural distance on log distance. Weights are the employment levels in the origin region.

Figure A3: Wages, migration and rents
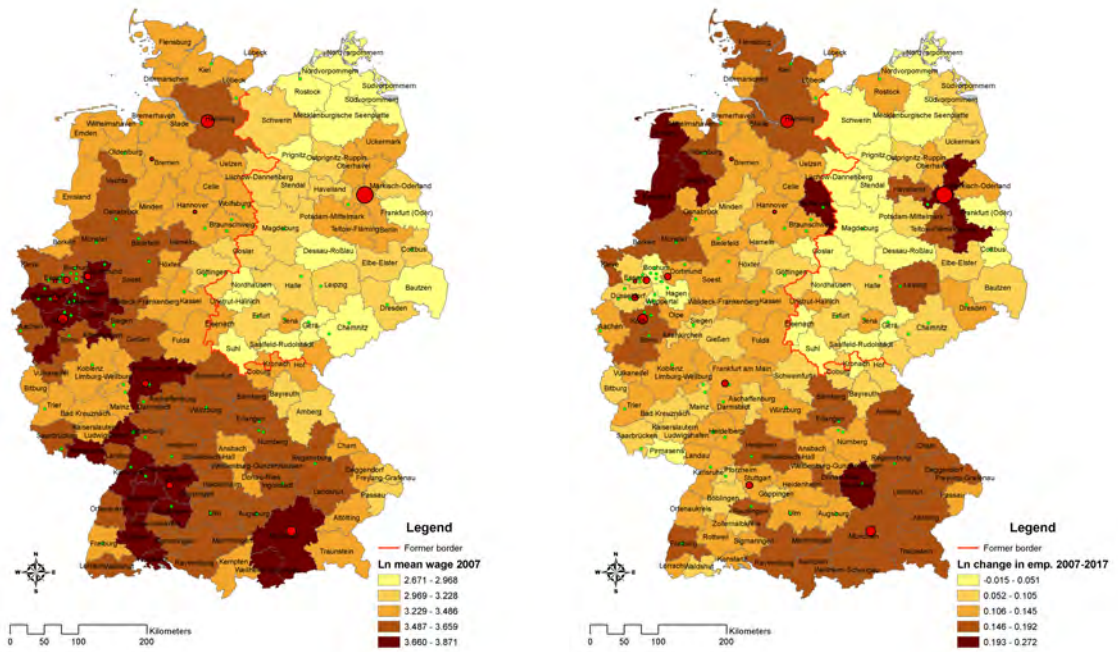
(a) Wages 2007

(b) Change in employment 2007-2017

(c) Change in rent 2007-2017

Note: Data from the IAB.

K Theory appendix

K.1 Housing market

In this appendix, we derive the formula for housing prices, equation (7) in the main text. We assume housing supply to follow a Cobb-Douglas production function as in equation (6) such that developers optimally choose capital and land inputs to maximize profits:

$$\pi_{i,t}^h = p_{i,t}\eta_{i,t}\left(\frac{\bar{T}_i}{\beta}\right)^{\beta}\left(\frac{K_{i,t}}{1-\beta}\right)^{1-\beta} - r_{i,t}^T \bar{T}_i - K_{i,t},$$

where we have normalized the internationally competitive interest rate for capital to unity and $r_{i,t}^T$ is the local rental rate for developable land. The Cobb-Douglas structure of the housing supply function implies that the local rental rate of land is decreasing in the amount of developable land available and increasing in capital usage:

$$r_{i,t}^T = \frac{\beta}{1-\beta}\frac{K_{i,t}}{\bar{T}_i}. \tag{31}$$

Landowners make zero profits, which implies that

$$p_{i,t} = \frac{(r_{i,t}^T)^{\beta}}{\eta_{i,t}}$$

Housing supply (6) is then increasing in TFP, land and house prices, such that the housing supply elasticity is $\frac{1-\beta}{\beta}$:

$$H_{i,t}^S = \eta_{i,t}^{\frac{1}{\beta}}\left(\frac{\bar{T}_i}{\beta}\right)p_{i,t}^{\frac{1-\beta}{\beta}}$$

Using equation (2) housing expenditures of workers in region i are given by $(1 - \alpha)(1-\iota)\sum_{\theta}L_{i,t}^{\theta}\varphi_{i,t}^{\theta} = (1-\alpha)(1-\iota)X_{i,t}$. Due to the Cobb-Douglas structure of housing supply, a constant fraction β of developers' income is spent on land rental, so $r_{i,t}^T\bar{T}_i = (1-\alpha)\beta(1-\iota)X_{i,t}$. Combining with equation (31) reveals that capital input is increasing in total housing expenditures:

$$K_{i,t} = (1-\beta)(1-\alpha)(1-\iota)X_{i,t}.$$

In equilibrium, housing demand equals housing supply such that

$$\eta_{i,t} \left(\frac{\bar{T}_i}{\beta} \right)^{\beta} \left((1-\alpha)(1-\iota)X_{i,t} \right)^{1-\beta} = \frac{(1-\alpha)(1-\iota)X_{i,t}}{p_{i,t}},$$

which leads to equation (7). House prices are larger in regions with higher total income, small land supply and small housing TFP. The effect of density on house prices can further be split into a supply side and a demand side effect:

$$p_{i,t} = \left(\frac{(1-\alpha)(1-\iota)\beta}{\eta_{i,t}^{\frac{1}{\beta}}} \right)^{\beta} \left[\sum_{\theta} \frac{L_{i,t}}{\bar{T}_i} \psi_{i,t}^{\theta} \left(\frac{L_{i,t}}{\bar{T}_i} \right)^{\kappa^{\theta}} \right]^{\beta} \tag{32}$$

The first term in the sum describes the effect of population density on the supply of housing: fixed supply of developable land translates into higher housing prices when immigration in i raises population. Population density increases productivity and in turn wages via agglomeration economies as well, which translates into higher housing demand (the third term in the sum). Using population density instead of output density as a regressor in equation (24), we would underestimate the true effect of density as a congestion force by the demand-side effect.

K.2 Derivation of equation (9)

The net present value of migration from region i to region j is given as

$$NPV_{ij|i,t+1}(\omega) = (1+\rho)^{-1} \frac{V_{j|i,t}^{\theta}(\omega)}{\exp(\tau_{ij}^{\theta})} + (1+\rho)^{-2}V_{j|i,t}^{\theta}(\omega) + \ldots + (1+\rho)^{-\mathcal{T}^{\theta}}V_{j|i,t}^{\theta}(\omega)$$

$$= \frac{V_{j|i,t}^{\theta}(\omega)}{\rho} \left[\frac{\rho}{(1+\rho)\exp(\tau_{ij}^{\theta})} + \frac{1}{1+\rho} - \frac{1}{(1+\rho)^{\mathcal{T}^{\theta}}} \right],$$

where $\rho \in (0,1)$ is the discount factor and $V_{j|i,t}$ is the constant utility flow as assumed by myopic individuals. We observe that $NPV_{ij|i,t+1}$ corresponds to an ordinary annuity as long as $\tau_{ij}^{\theta} = 0$, that is if workers do not migrate to another region. We then define

$$m_{ij}^{\theta} \equiv \frac{1}{1+\rho} \left[\frac{1}{\exp(\tau_{ij}^{\theta})} + \frac{(1+\rho)^{\mathcal{T}^{\theta}-1} - 1}{\rho(1+\rho)^{\mathcal{T}^{\theta}-1}} \right] > 1$$

as the migration cost adjusted multiplier of per-period indirect utility which is decreasing in bilateral migration costs. These results lead to equation (9).

K.3 Expected utilities and migration probabilities

K.3.1 Distribution of utilities

To derive the distribution of utility we first define as $F_{ij,t}^{\theta}(u)$ the probability that region $j \in J$ offers a net present value of life-time utility smaller than u to a worker ω located in region i:

$$F_{ij,t}^{\theta}(u) \equiv Pr\left\{(1-\iota)m_{ij}^{\theta}\frac{A_{j,t}^{\theta}w_{j,t}^{\theta}a_{ij,t}^{\theta}(\omega)}{\left(p_{j,t}^{h}\right)^{1-\alpha}} \leq u\right\} = Pr\left\{a_{ij,t}^{\theta}(\omega) \leq \frac{\left(p_{j,t}^{h}\right)^{1-\alpha}}{A_{j,t}^{\theta}(1-\iota)w_{j,t}^{\theta}m_{ij}^{\theta}}u\right\}$$

As the idiosyncratic amenity shock is Fréchet distributed according to equation (8), we have

$$F_{ij,t}^{\theta}(u) = \exp\left[-B_{ij,t}^{\theta}\left(\frac{\left(p_{j,t}^{h}\right)^{1-\alpha}}{A_{j,t}^{\theta}(1-\iota)w_{j,t}^{\theta}m_{ij}^{\theta}}u\right)^{-\gamma^{\theta}}\right] = \exp\left[-\Omega_{ij,t}^{\theta}u^{-\gamma^{\theta}}\right] \quad (33)$$

with $\Omega_{ij,t}^{\theta} = B_{ij,t}^{\theta}\left(A_{j,t}^{\theta}(1-\iota)w_{j,t}^{\theta}m_{ij}^{\theta}/\left(p_{j,t}^{h}\right)^{1-\alpha}\right)^{\gamma^{\theta}}$. Each worker located in region i chooses the destination that gives her the highest net present value of life-time utility (9) as a function of amenity shocks $a_{ij,t}^{\theta}(\omega)$. Using equation (33), the probability that a worker ω in region i gets a discounted life-time utility smaller than u, $F_{i,t}^{\theta}(u)$, is

$$F_{i,t}^{\theta}(u) = \prod_{j\in J}F_{ij,t}^{\theta}(u) = \exp\left[-\Omega_{i,t}^{\theta}u^{-\gamma^{\theta}}\right], \quad (34)$$

where $\Omega_{i,t}^{\theta} = \sum_{j\in J}\Omega_{ij,t}^{\theta}$. Equation (34) defines the distribution of utilities across workers of group θ located in region i at time period t.

K.3.2 Expected utility

Expected utility of group-θ individuals located in region i is then given by

$$E_{i,t}^{\theta}[u] = \int_{0}^{\infty}u dF_{i,t}^{\theta}(u) = \int_{0}^{\infty}\Omega_{i,t}^{\theta}\gamma^{\theta}u^{-\gamma^{\theta}}\exp\left[-\Omega_{i,t}^{\theta}u^{-\gamma^{\theta}}\right]du. \quad (35)$$

Redefining the variables such that

$$y_{i,t}^{\theta} = \Omega_{i,t}^{\theta}u^{-\gamma^{\theta}} \qquad \text{and} \qquad dy_{i,t}^{\theta} = -\gamma^{\theta}\Omega_{i,t}^{\theta}u^{-\gamma^{\theta}-1}du,$$

we can rewrite equation (35) as:

$$E_{i,t}^\theta[u] = \int_0^\infty \left(\Omega_{i,t}^\theta\right)^{\frac{1}{\gamma^\theta}} \left(y_{i,t}^\theta\right)^{-\frac{1}{\gamma^\theta}} exp\left[-y_{i,t}^\theta\right]dy_{i,t}^\theta = \left(\Omega_{i,t}^\theta\right)^{\frac{1}{\gamma^\theta}} \Gamma\left(\frac{\gamma^\theta - 1}{\gamma^\theta}\right), \qquad (36)$$

where $\Gamma\left(\frac{\gamma^\theta-1}{\gamma^\theta}\right)$ is the Gamma function. Plugging in the definition for $\Omega_{i,t}^\theta$ yields equation (13).

K.3.3   Conditional migration probability (11)

In the following, we show how the probabilities of migrating to a region j conditional on living in region i are derived from the properties of the Fréchet distribution. The probability that region j offers the highest utility among all $j \in J$ conditional on living in region i (which is equal to the migration probability from i to j) results as

$$\begin{aligned}
\chi_{ij|i,t}^\theta &= Pr\{V_{ij|i,t}^\theta(\omega)m_{ij}^\theta \geq \max_{n\in J\backslash j} V_{in|i,t}^\theta(\omega)m_{ij}^\theta\} \\
&= \int_0^\infty \prod_{n\in J\backslash j} F_{in,t}^\theta(u) f_{ij,t}^\theta(u)du \\
&= \int_0^\infty \gamma^\theta \Omega_{ij,t}^\theta u^{-\gamma^\theta-1} e^{-\Omega_{i,t}^\theta u^{-\gamma^\theta}} du \\
&= \Omega_{ij,t}^\theta \int_0^\infty \frac{d}{du}\left[\frac{1}{\Omega_{i,t}^\theta} e^{-\Omega_{i,t}^\theta u^{-\gamma^\theta}}\right] du = \frac{\Omega_{ij,t}^\theta}{\Omega_{i,t}^\theta},
\end{aligned}$$

where $f_{ij,t}^\theta(u)$ describes the density function.

K.4   Derivation of equation (30)

We start with a social welfare function that allows for inequality aversion in a general form. Following Atkinson (1970), we assume

$$\mathcal{W} = \frac{1}{1-\varepsilon} \sum_i \sum_\theta \left(\mathcal{U}_i^\theta\right)^{1-\varepsilon} \frac{L_i^\theta}{\bar{L}} \qquad (37)$$

for both the baseline ($*$) and the counterfactual (c) spatial equilibrium. The degree of inequality aversion is measured by $0 \leq \varepsilon \neq 1$ as explained in Section G.3.[14]

It is instructive to transform equation (37) into a scale-dependent part $\mathcal{U}$ and a scale-independent part that penalizes for inequality $1 - \mathcal{I}$. The former is simply the weighted average of location-group utility that for the baseline and the counterfac-

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[14]We obtain log-utility as a special case for $\epsilon = 1$.

tual is respectively given by:

$$\mathcal{U}^* = \sum_i \sum_\theta \mathcal{U}_i^{\theta*} \frac{L_i^{\theta*}}{\bar{\bar{L}}} \tag{38}$$

$$\mathcal{U}^c = \sum_i \sum_\theta \widehat{\mathcal{U}_i^\theta} \mathcal{U}_i^{\theta*} \frac{L_i^{\theta*}}{\bar{\bar{L}}}. \tag{39}$$

Using the "exact hat algebra" approach by Dekle et al. (2007), we express group-region utility in the counterfactual measured at the migration origin as $\widehat{\mathcal{U}_i^\theta} \mathcal{U}_i^{\theta*}$. This way, we account for changes in expected utility and migration costs which enter into $\widehat{\mathcal{U}_i^\theta}$ via equations (27) and (28).

To derive the inequality measure $\mathcal{I}$, we search for the *equally distributed equivalent utility* $\mathcal{U}_{EDE}$ (a hypothetical average level of expected lifetime utility across individuals) that leads to the same level of welfare as with the actual distribution of expected lifetime utilities. Equation (37) implies that

$$\mathcal{W}(\mathcal{U}_{EDE}) = \frac{1}{1-\varepsilon}(\mathcal{U}_{EDE})^{1-\varepsilon}, \tag{40}$$

so we can solve for $\mathcal{U}_{EDE}$ by equalizing equations (37) and (40). This yields

$$\mathcal{U}_{EDE} = \left[\sum_i \sum_\theta \left(\mathcal{U}_i^\theta\right)^{1-\varepsilon} \frac{L_i^\theta}{\bar{\bar{L}}} \right]^{\frac{1}{1-\varepsilon}}.$$

Using Atkinson's inequality measure

$$\mathcal{I} = 1 - \frac{\mathcal{U}_{EDE}}{\mathcal{U}} \qquad \in [0,1], \tag{41}$$

we obtain

$$\mathcal{I}^* = 1 - \left[\sum_i \sum_\theta \left(\frac{\mathcal{U}_i^{\theta*}}{\mathcal{U}^*}\right)^{(1-\varepsilon)} \frac{L_i^{\theta*}}{\bar{\bar{L}}} \right]^{\frac{1}{1-\varepsilon}} \tag{42}$$

$$\mathcal{I}^c = 1 - \left[\sum_i \sum_\theta \left(\frac{\widehat{\mathcal{U}_i^\theta} \mathcal{U}_i^{\theta*}}{\mathcal{U}^c}\right)^{(1-\varepsilon)} \frac{L_i^{\theta*}}{\bar{\bar{L}}} \right]^{\frac{1}{1-\varepsilon}} \tag{43}$$

for both the baseline and the counterfactual case, respectively. These derivations allow us to reformulate equation (37) as $\mathcal{W} = \mathcal{U}(1 - \mathcal{I})$ and express changes in social welfare according to equation (30).

Figure A4 illustrates the quantitative effect of ϵ on $1 - \mathcal{I}^*$ which gives the fraction of aggregate utility remaining after stripping off the social cost of inequality. While

the right panel uses individual utility levels according to equation (42), we replace utility with nominal wages in the left panel. In both panels, the underlying distributions are from the spatial equilibrium with migration costs (see Section F). We observe that $1 - \mathcal{I}^* = 1$ for $\epsilon = 0$, but declines in the value of the inequality parameter in both cases. We further observe that inequality in our model is driven by a group- and a region-specific component. In the absence of migration costs, however, there would be perfect arbitrage within groups so inequality would only result from differences across regions due to a different composition of groups across locations. We highlight three values of ε in Figure A4 which we use in the applications in the next section. By design, there is no inequality penalty in the utilitarian case ($\varepsilon = 0$). The penalty in social welfare amounts to one third for $\varepsilon = 0.5$ and to more than two thirds for $\varepsilon = 2$. These penalties are lower for nominal wages indicating that inequality is more pronounced for expected utility.

Figure A4: Relative social welfare after adjusting for inequality
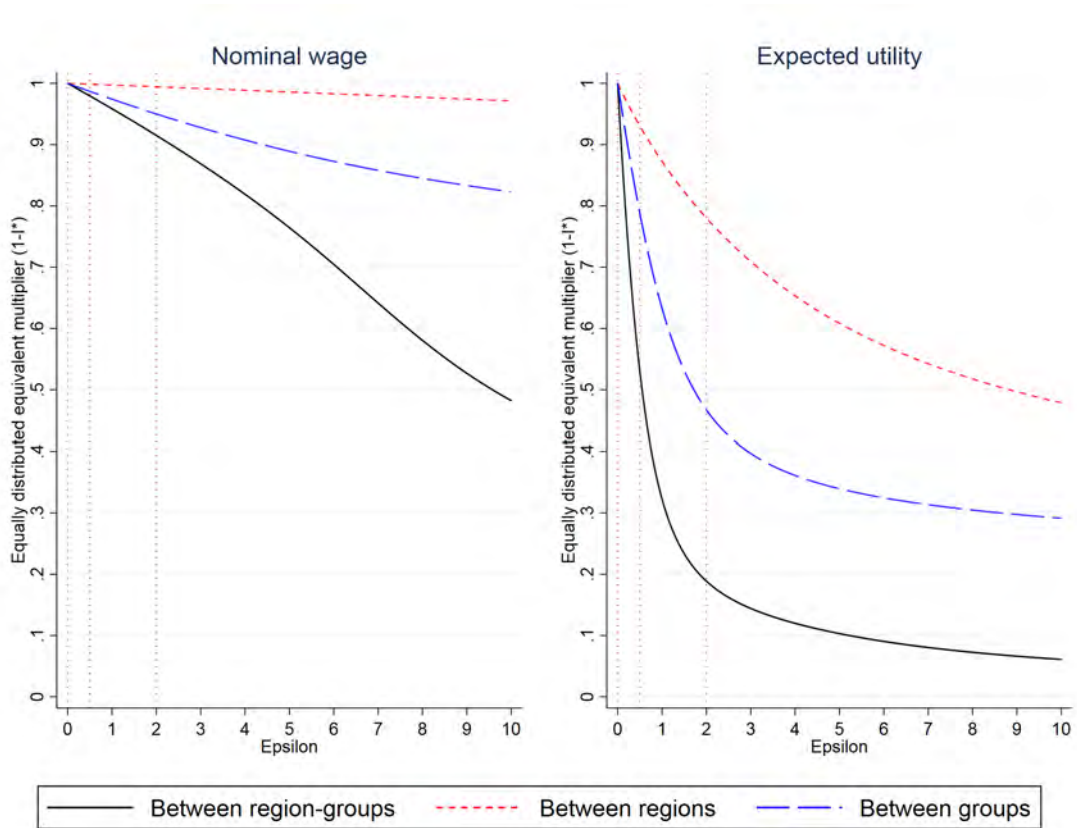
Notes: The figure illustrates how the relative social welfare after adjusting for inequality (using Atkinson's inequality measure $\mathcal{I}^*$) depends on the inequality aversion parameter $1 - \mathcal{I}^*$. To this end, we use variation in nominal wage or expected utility and across region-groups, regions (using mean values within groups), and groups (using mean values across regions) as inputs. Nominal wage and expected utility are from the spatial equilibrium derived in Section F.

L Data appendix

This section provides additional information about the data sets used in the empirical analysis.

L.1 Summary statistics

The below table provides descriptive statistics for the central variables using in the identification of our model.

Table 9: Summary statistics

	N	Mean	Std dev
Migration flow	3936438	72.65	1767.32
Migration probability	3936438	0.01	0.08
Distance (in km)	3936438	317.24	157.38
Cultural distance	3936438	67.48	11.52
Employment	27918	10385.28	19703.88
Average daily wage	27918	82.25	32.30
House purchase price (in $€/m^2$)	1551	1303.82	540.73
Employment density	1551	77.75	81.43
Output density	1551	6901.70	7975.30
1907 population density	141	141.42	173.58
Employment share: female (in %)	1551	45.42	3.27
Employment share: tertiary education (in %)	1551	13.58	4.60
Employment share: no apprenticeship (in %)	1551	10.61	3.18
Employment share: 16-30 years (in %)	1551	23.05	2.79
Employment share: 51-65 years (in %)	1551	26.09	4.90

Notes: Summary statistics cover the period 2007-2017. Migration probabilities are computed using lagged employment. Numbers of observations differ as we have 141 regions, 141 (regions) x 18 (groups) = 1551 region-groups, and 1551^2 bilateral region-group combinations.

L.2 Migration

Bilateral migration flows are constructed from individual-level information about the place of employment in years t and $t + 1$. Computation of these flows therefore requires that individuals can be observed on an annual basis from their first until their last appearance in the BeH. Since there is not necessarily an employment record for each individual in every year,[15] we close such gaps by creating artificial records that duplicate the last available employment record and, in particular, the place of

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[15]This would be the case if a person was in a different form of employment that is not subject to social security contributions, unemployed or had withdrawn from the labour market.

employment. In doing so, we implicitly assume that a person remains in the same labour market region when there is no employment record.[16]

L.3 Productivity index

Group-region-year specific productivity is estimated from a model in which log daily wages are regressed against individual fixed effects, group-region-year dummies as well as indicators for working part-time and being an apprentice over the period 1993-2017. For computational purposes we remove all observations of individuals who never change their place of employment and estimate the model separately by gender. Table 10 shows that part-time workers have daily earnings that are smaller by approximately 31% (=exp(-0.368)-1) than those of full-time workers if they are female and 39% (=exp(-0.487)-1) if they are male. Adding occupational and sector dummies to the model only slightly reduces the magnitude of these effects. Table 11 provides an overview of the differences in the estimated productivities across groups. Ceteris paribus, productivity is lower among females than males while it increases with the skill level and falls with age.

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[16]Notice that this procedure is only used for the computation of migration flows. Estimation of individual-level productivity is therefore unaffected. Approximately 19% of the employment records in the data set are constructed in this way.

Table 10: Estimation of group-region-year productivity

	(1) Female	(2) Female	(3) Male	(4) Male
Part-time	-0.368*** (0.00)	-0.356*** (0.00)	-0.487*** (0.00)	-0.448*** (0.00)
Apprentice	-0.805*** (0.00)	-0.812*** (0.00)	-0.963*** (0.00)	-0.975*** (0.00)
Constant	4.192*** (0.00)	4.189*** (0.00)	4.446*** (0.00)	4.445*** (0.00)
Individual effects	Yes	Yes	Yes	Yes
Group-region-year effects	Yes	Yes	Yes	Yes
Occupation effects	No	Yes	No	Yes
Sector effects	No	Yes	No	Yes
r2	.786	.798	.851	.865
N	1,793,035	1,793,035	2,809,019	2,809,019

Notes: Units of observation are individual-level employment records. The dependent variable is the log average daily wage. Occupation dummies cover 86 different categories (Berufsgruppe, Klassifikation der Berufe 1988); sector dummies cover 88 different categories (Abteilungen, Klassifikation der Wirtschaftszweige 2008). $^{+}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Productivity differences

	(1) Group-region-year productivity
Female	-0.008*** (0.00)
31-50 years	-0.082*** (0.00)
51-65 years	-0.138*** (0.00)
Apprenticeship	0.067*** (0.00)
Tertiary education	0.293*** (0.00)
Constant	0.090*** (0.00)
Region effects	Yes
Year effects	Yes
r2	.889
N	27914

Notes: Units of observation are group-region-year cells. The dependent variable is a group-region-year-specific productivity measure that is derived as a fixed effect from an individual-level regression of log daily wages that also controls for individual fixed effects. $^{+}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

L.4   Housing price index

To compute mix-adjusted indices of purchase prices for a panel of labour market area-year observations, we use the methodology described in section D.5 and the "Real-Estate Data for Germany (RWI-GEO-RED)" micro data discussed in detail by Boelmann and Schaffner (2019). The data originally come from the internet platform ImmobilienScout24 and have been processed and made available for scientific research by the FDZ (Forschungsdatenzentrum) Ruhr. It covers apartments and houses for sale from 2007 to 2017. ImmobilienScout24 is the leading online platform for real estate listings, with a self-reported market share of about 50% (Georgi and Barkow, 2010).

The processed data contain a detailed geo-reference, accurate to the level of 1x1 square kilometer grid cells in the European standard ETRS89-LAEA projection. This makes it straightforward to calculate the straight-line distance from a property to the centre of a labour market area, defined as the geographic centroid of the municipality with the largest employment number. Moreover, the data set contains a wide range of property characteristics. However, the degree of coverage varies significantly, with missing values accounting for the majority of observations for selected variables. We focus on control variables with reasonably wide coverage, which include attributes that are typical in hedonic analyses such as the floor area, the number of rooms, the type of property (house vs. flat), the type of heating

system and whether features such a balcony, a garden, or a basement belong to the property. There are a limited number of missing variables within these variables. For each variable, we set the missing values to zero and generate an auxiliary indicator variable that identifies all observations with a missing value in the selected variable. The mix-adjusted hedonic index we generate then gives the price of a property with the national average in observable characteristics and the average unobserved characteristics of properties with non-missing values in observables, which is located right at the centre of the labour market area. We report summary statistics of observable characteristics in Table L.4. The average property has a floor area of about 80 square meters, approximately three rooms, and a 94.4-percent chance of being an apartment.

Table 12: House price index: Descriptive statistics

	N	mean	sd	p10	p90
Price per square meter	16,591,919	2,317	225,608	714	3,258
Distance to CBD (in km)	16,591,919	17.45	13.4	2.89	35.98
Living space (in square meter)	16,591,919	141.81	130.13	59	232
Rooms	16,591,919	4.75	2.77	2	8
Type of housing	16,591,919	0.4	0.49	0	1
Balcony	16,591,919	0.28	0.45	0	1
Garden	16,591,919	0.08	0.27	0	0
Basement	16,591,919	0.35	0.48	0	1
Type of heating	16,591,919	7.1	6.14	0	13

Notes: *Type of heating* is a categorical variable between 1 and 13. *Type of housing* is a binary variable with value one for apartments and zero for houses. *Balcony*, *Garden* and *Basement* are also binary variables. Micro data from RWI-Leibniz Institute for Economic Research (Boelmann and Schaffner, 2018).

M Map appendix

In this section we map the distribution of a) endogenous variables as observed in the data, b) exogenous variable as identified from the data using the structure of the model and c) equilibrium values of endogenous variables solved for using the structure of the model.

M.1 Endogenous variables observed in the data

In the below, we illustrate the spatial distribution of selected endogenous variables used in the identification of the model.

Figure A1: Mean wage 2017
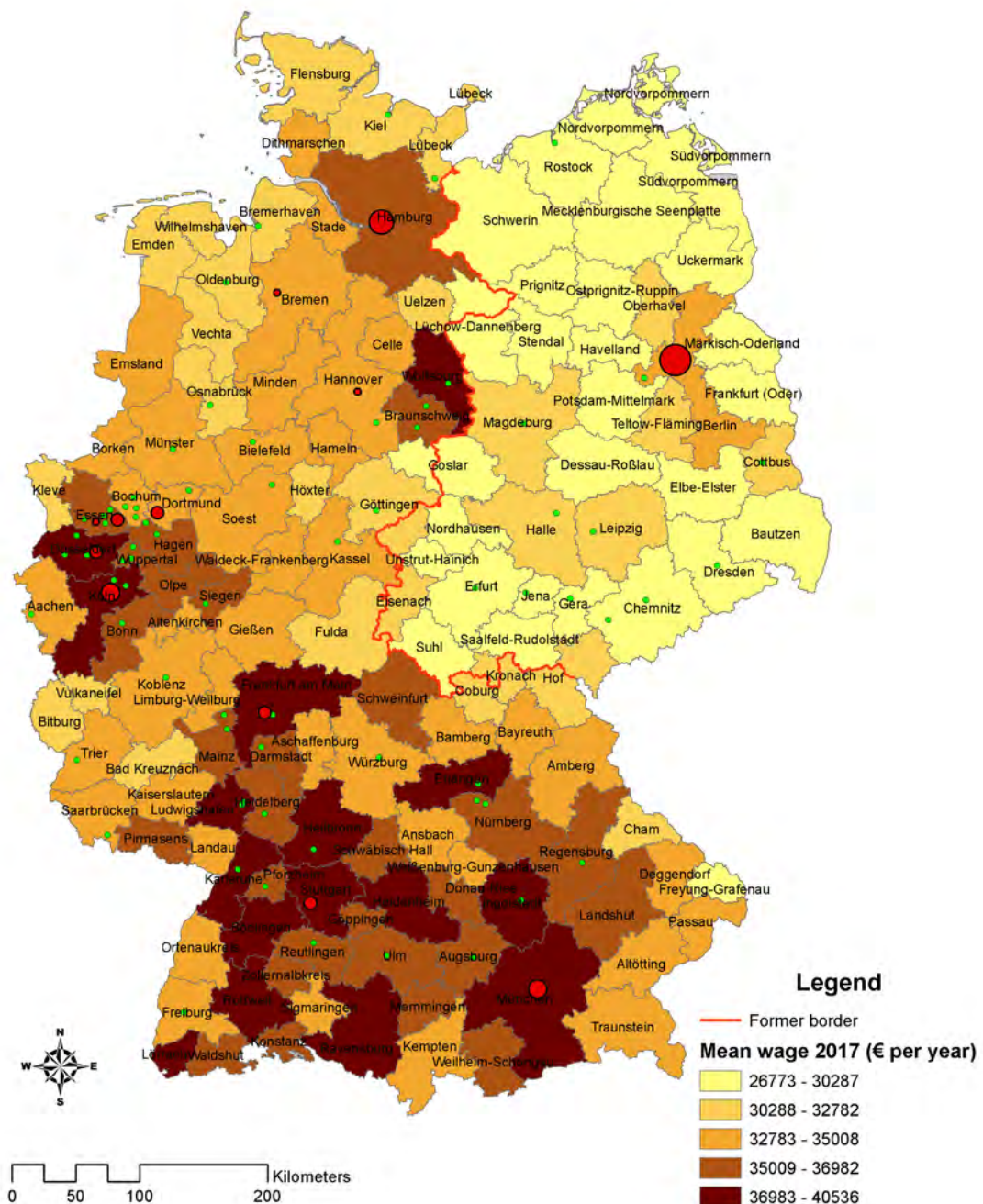
Notes: Aveage wage from the employment bibliography IAB data.
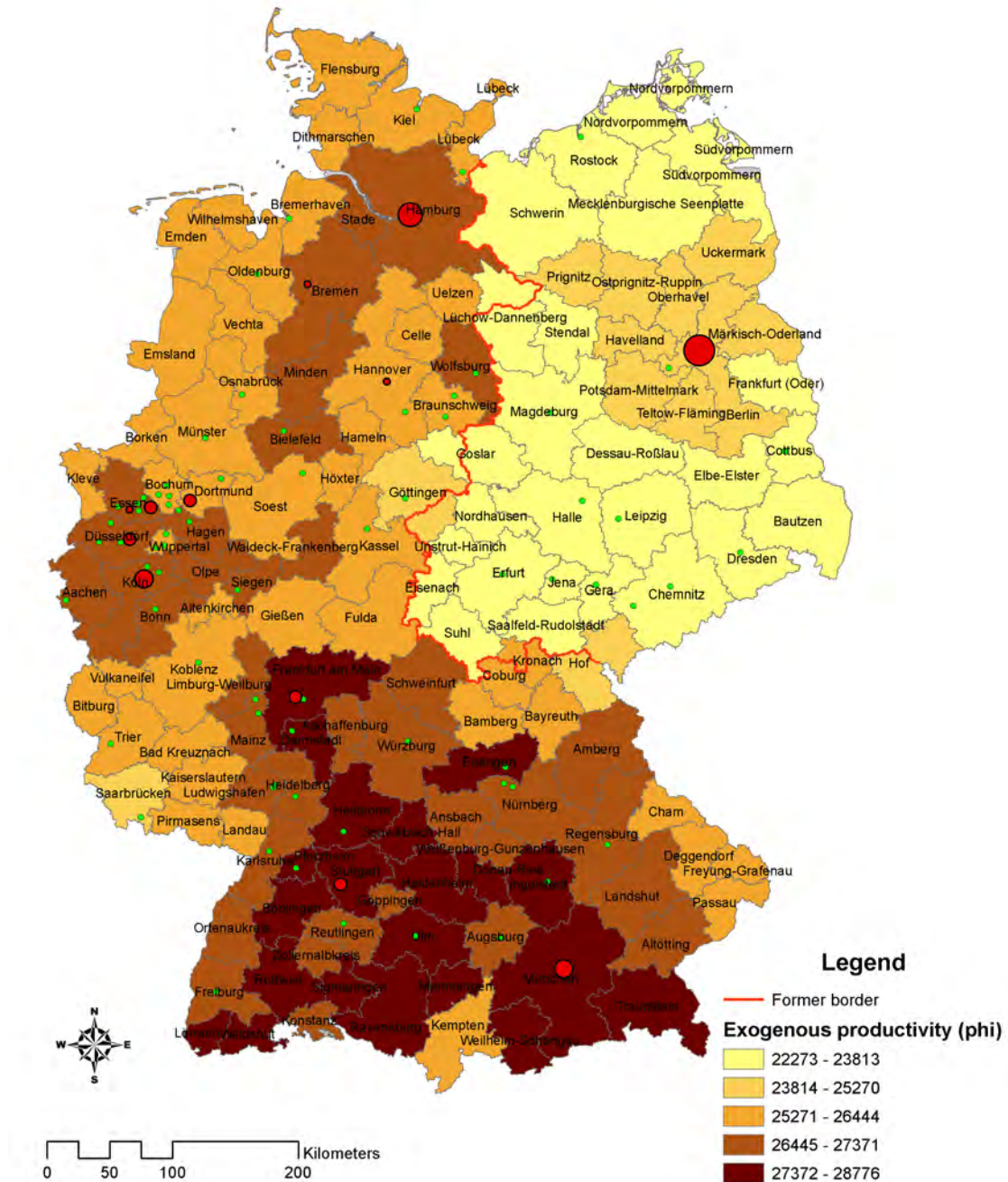
Figure A2: Housing cost 2017

Notes: Annualized housing cost based on micro data data on property prices from RWI (Boelmann and Schaffner, 2018) and the methodology described in section D.5

M.2 Exogenous variables

In the below, we present the spatial distribution of selected exogenous variables identified using the observed endogenous variables and the structure of the model.

Figure A3: Exogenous productivity

Notes: Exogenous productivity is identified from the regression of the log of AKM-adjusted wages against the log of employment density controlling for zone effects and using 1907 log population density as an instrument. We map the regional averages across all groups and years.

Figure A4: Housing TFP
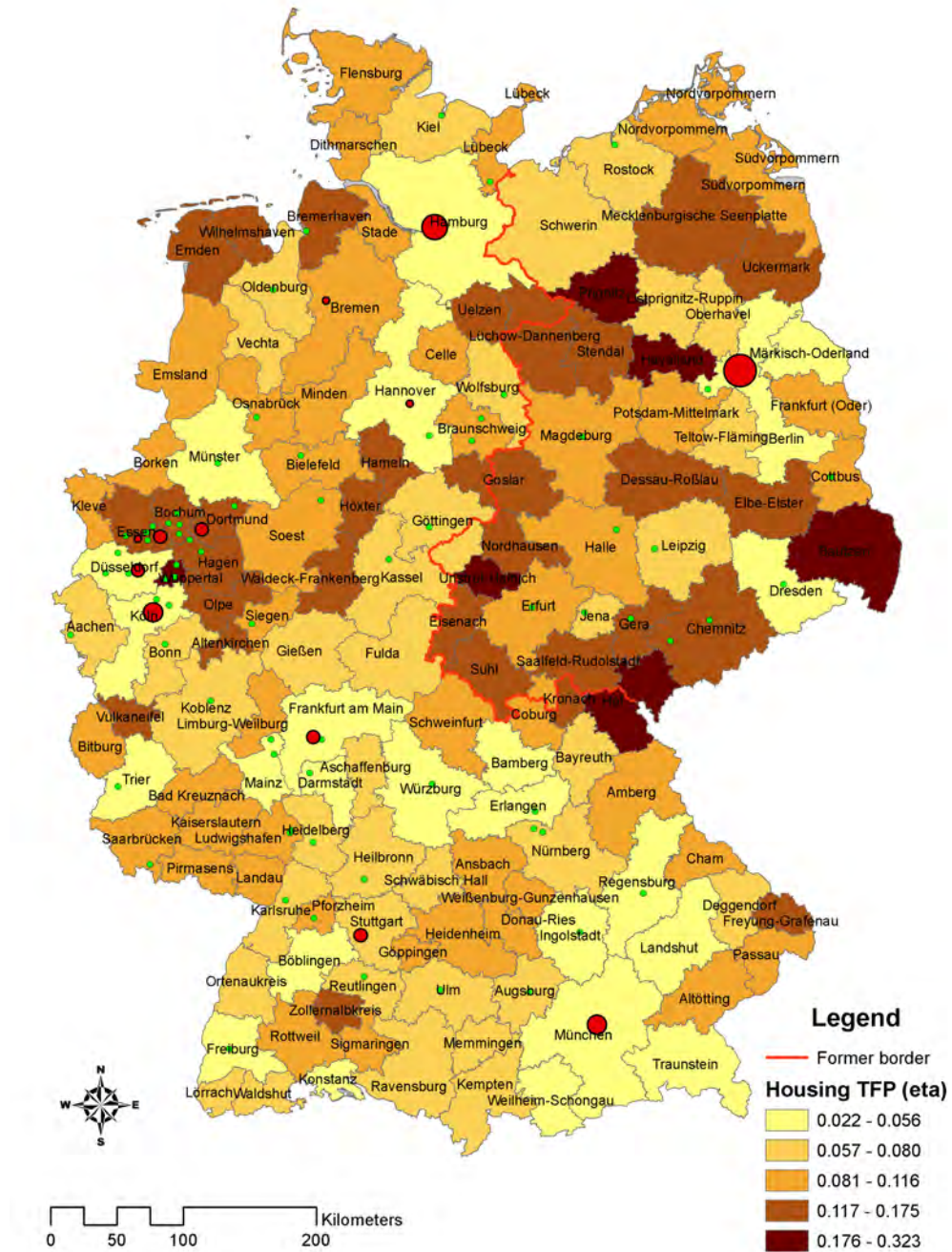
Notes: Housing TFP is identified from the structural regression of the log of regional house prices against the log of regional output density controlling for zone effects and using 1907 log population density as an instrument. Regional house prices are an index based on micro data data on property prices from RWI (Boelmann and Schaffner, 2018) and the methodology described in section D.5. We map the regional averages across all years.
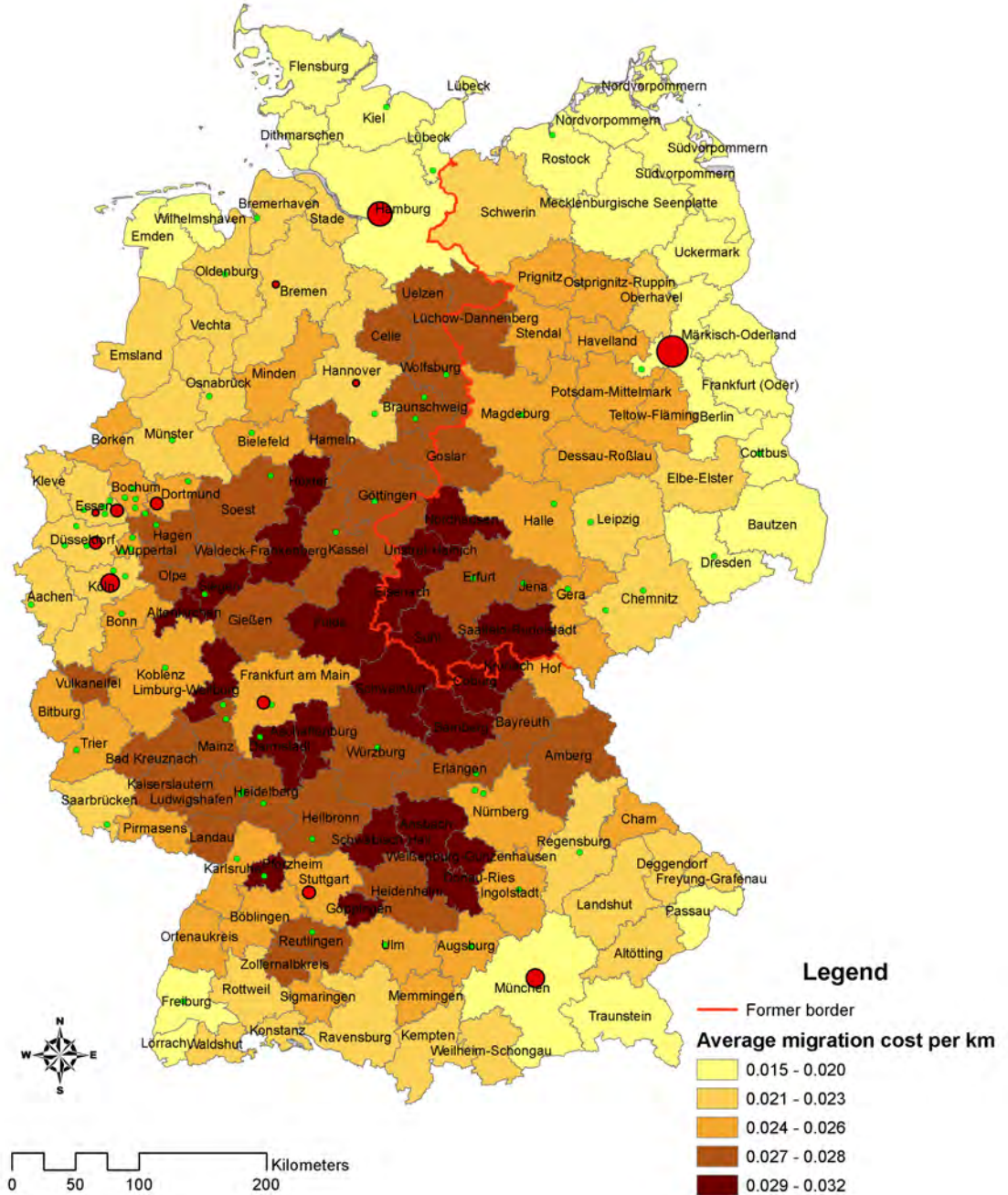
Figure A5: Exogenous amenity
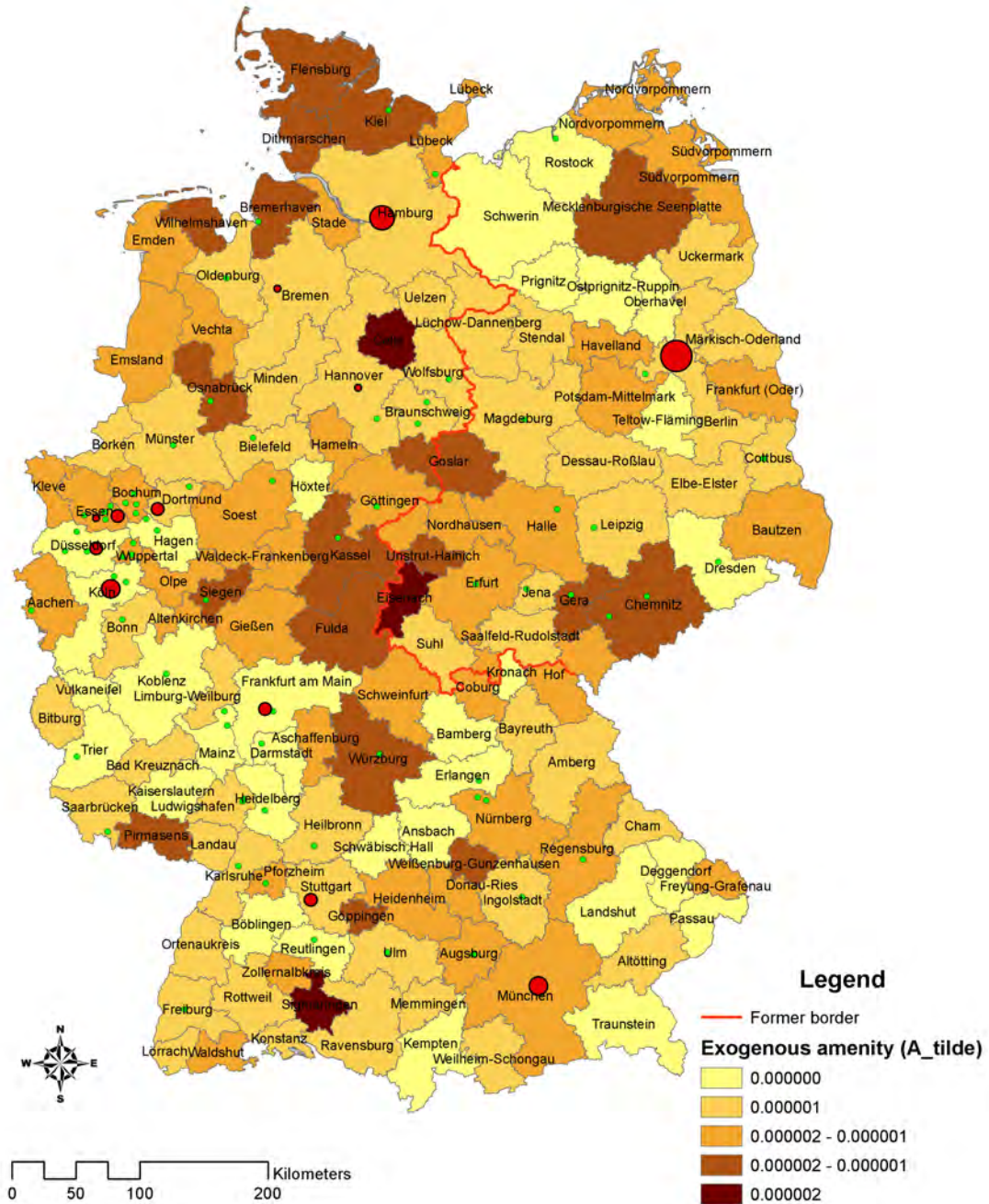
Notes: Exogenous amenity is identified from the regression of the structural residual from the amenity heterogeneity regression (21) against the log of employment density controlling for zone effects and using 1907 log population density as an instrument. The structural residual is from a regression of destination effects from the migration gravity equation (20) against the log of wage over housing cost. We map the regional averages across all groups and years.

Figure A6: Average migration cost
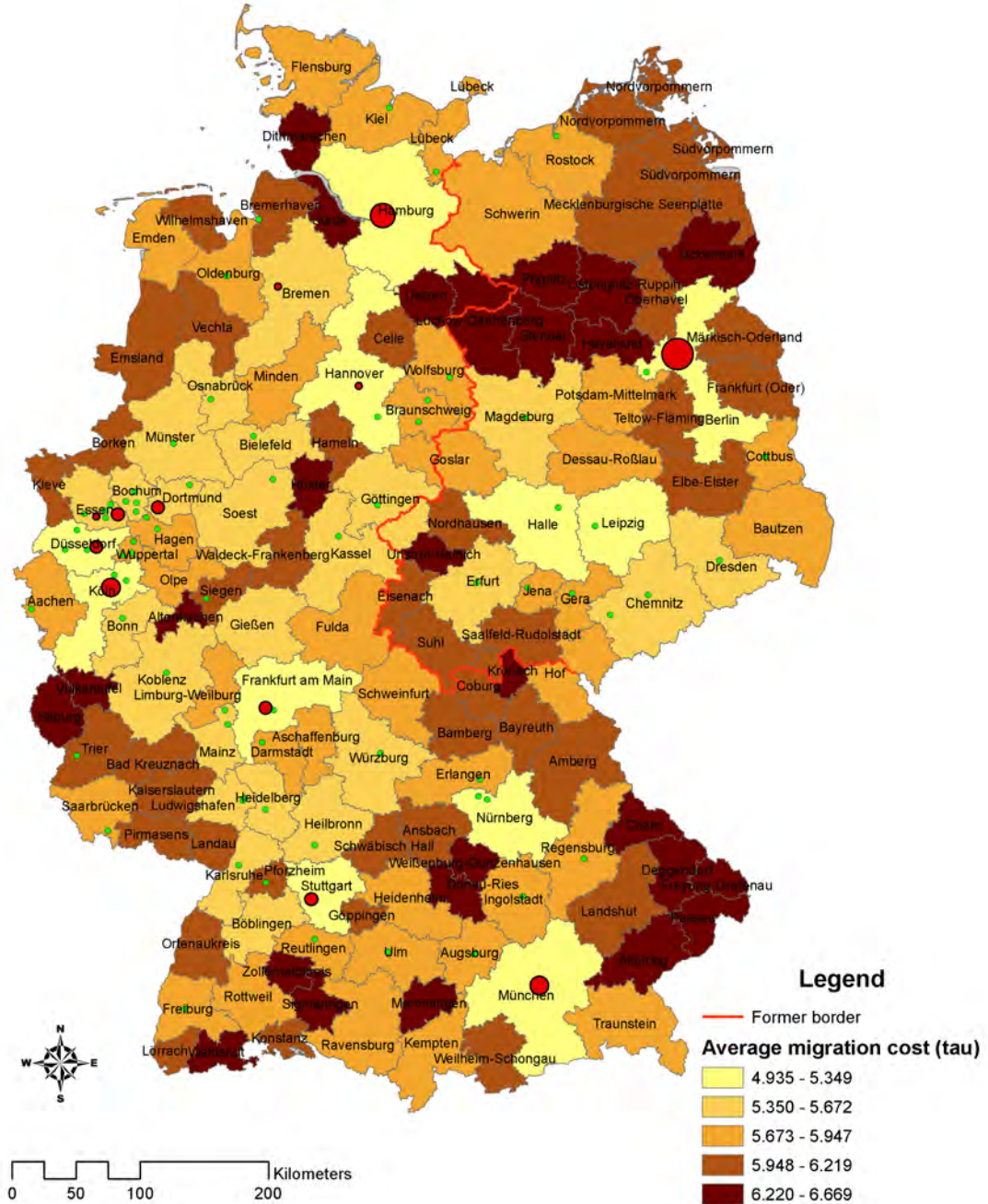
Notes: Migration cost is the origin-destination effect τ_{ij}^{θ} from migration gravity equation (20) controlling for origin-year and destination-year effects, adjusted for amenity heterogeneity (captured by γ^{θ}). We map the regional averages across all destinations, groups and years.

Figure A7: Average migration cost per km

Legend

— Former border

Average migration cost per km

▢	0.015 - 0.020
▢	0.021 - 0.023
▢	0.024 - 0.026
▢	0.027 - 0.028
▢	0.029 - 0.032

Notes: Migration cost per km is the origin-destination effect τ_{ij}^{θ} from migration gravity equation (20) controlling for origin-year and destination-year effects, adjusted for amenity heterogeneity (captured by γ^{θ}) and divided by the distance between an origin-destination pair. We map the regional averages across all destinations, groups and years.

N   Identification appendix

N.1   Overidentification

In this section, we correlate the exogenous variables with observable characteristics not used for identification. For one thing, we compare τ_{ij} to observable measures of migration distances. For another, we compare exogenous productivity, amenity and housing TFP to observable locational characteristics.

To connect to a literature on determinants of migration costs, we decompose τ_{ij}^{θ} into observable $Z'_{ij}b$ and unobservable $e_{ij}^{m\theta}$ effects according to

$$\tau_{ij}^{\theta} = Z'_{ij}b^{\theta} + e_{ij}^{m\theta}, \tag{44}$$

where Z'_{ij} is a vector of various dimensions of migration distance and b^{θ} is a vector of the corresponding group-specific marginal effects. As a measure of cultural distance we use the language similarity index by Falck et al. (2012) re-scale it as follows: Cultural distance = 100 - linguistic similarity.

Table 13: Determinant of migration costs

	(1) Ln migration cost (τ)	(2) Ln migration cost (τ)	(3) Ln migration cost (τ)
Ln physical distance	1.134*** (0.00)		1.100*** (0.01)
Ln cultural distance		3.381*** (0.01)	0.153*** (0.02)
r2	.92	.901	.92
N	355,320	355,320	355,320

Notes: Unit of observation origin-destination-group. Models include origin, destination and group fixed effects. Standard errors in parentheses. $^{+}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

O   Spatial equilibrium appendix

Below, we correlate the spatial equilibrium values of selected endogenous variables identified in Section F with the values observed in the data.

Figure A1: Spatial equilibrium vs. observed values

(a) Ln density

(b) Ln wage

(c) Ln housing costs

(d) Ln high-skilled share
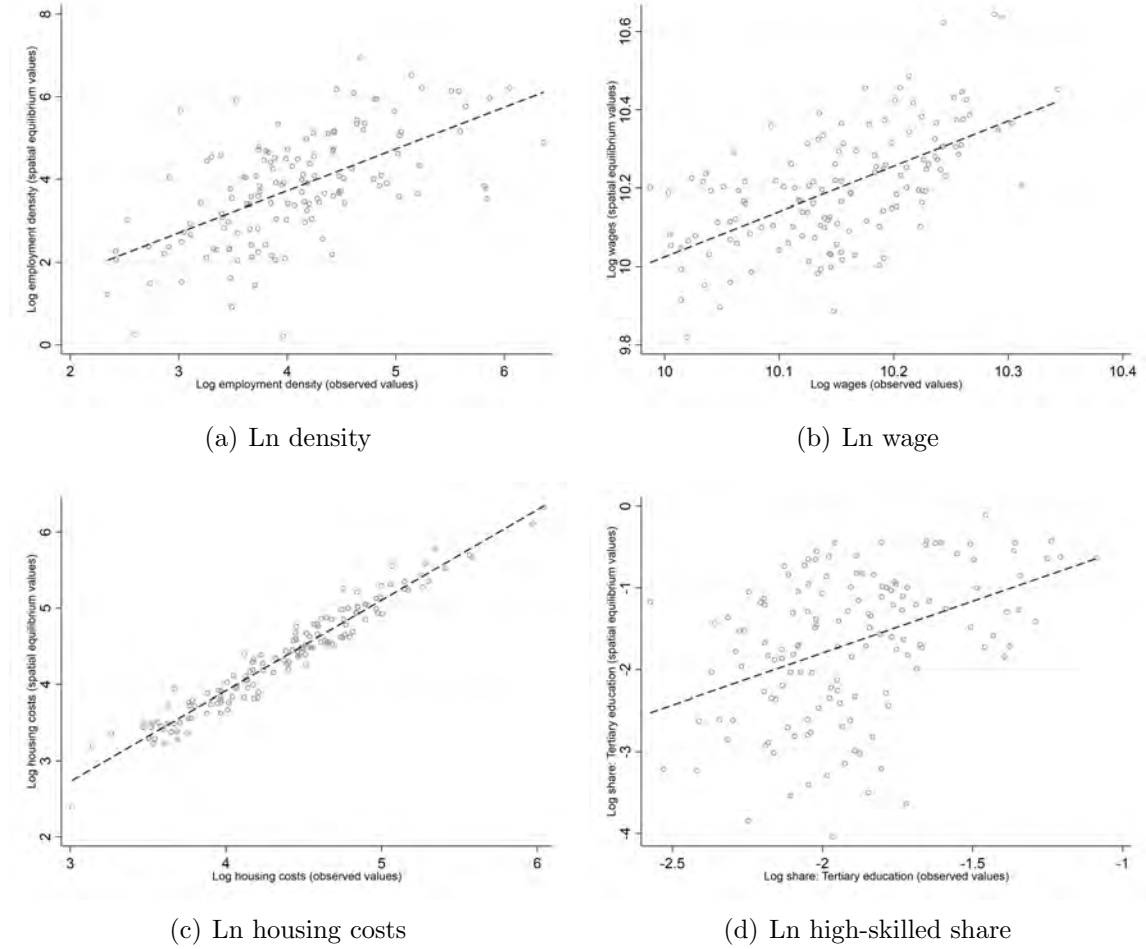
Note: Each panel correlates the values for an endogenous variable in the spatial equilibrium with migration costs solved in Section O with the observed realizations in the data.

P Applications appendix

P.1 Trade shocks

This section adds to Section H.1 in the main paper in which we discuss the general equilibrium effects of trade shocks. We present ancillary estimates of trade exposure effects on productivity, which we input as exogenous shocks into our model. We also map the distribution of the exogenous shock on productivity and the effects on the endogenous variables wages, housing costs, and utility based on the model-based counterfactuals discussed in Section H.1.

In Table 14, we regress exogenous productivity $\psi_{i,t}^{\theta}$ recovered according to equation (23) against measures of trade exposure that we construct in following Dauth et al. (2014) for our labour market areas. These measures capture the increase in import and export exposure originating from increasing trade with Eastern Europe and China over the 1998-2008 period. In keeping with intuition and the results in Dauth et al. (2014), column (1) reveals that productivity changes are positively associated with increases in export exposure and negatively correlated with changes in import exposure. In column (2), we control for group effects and mean reversion via the initial 1998 productivity level. The r2 increases substantially, but the estimated coefficients remain within relatively close range, revealing that the additional controls are strong and orthogonal to the variables of interest. In column (3) we allow for a full set of interactions between 18 group dummies and the two exposure measures. To keep the presentation compact, we do not report all the estimated coefficients. Instead, in column (4) we regress the predicted exposure effects from (3) against indicator variables for skill, gender, and age variables, as well as an indicator variable for the eastern region. In keeping with intuition, the increasing trade exposure seems to have favoured skilled and, in particular, highly skilled workers. In contrast, female and older workers benefit less. On average, the trade shock was less favorable to the eastern than to the western regions. We take these predicted effects on productivity as an exogenous shock whose consequences we evaluate in Section H.1.

Table 14: Trade exposure and exogenous productivity

	(1) Ln change in exogenous productivity (1998-2008)	(2) Ln change in exogenous productivity (1998-2008)	(3) Ln change in exogenous productivity (1998-2008)	(4) Ln predicted trade exposure effect (1998-2008)
Import measure (1998-2008)	-0.007*	-0.004$^+$		
	(0.00)	(0.00)		
Export measure (1998-2008)	0.007*	0.010***		
	(0.00)	(0.00)		
Exog. prod. ψ (1998, in 1000 €)		-0.035***	-0.035***	0.000**
		(0.00)	(0.00)	(0.00)
Apprenticeship				0.012***
				(0.00)
Tertiary education				0.020***
				(0.00)
Female				-0.025***
				(0.00)
31-50 years				0.003*
				(0.00)
51-65 years				-0.034***
				(0.00)
East				-0.007***
				(0.00)
Ln density				-0.000
				(0.00)
Group effects	-	Yes	Yes	-
Group-exposure interactions	-	-	Yes	-
N	2538	2538	2538	2538
r2	.00146	.462	.469	.304

Notes: Unit of observation is region-group. Change in exogenous productivity are residualized (controlling for worker fixed effects and labour-market area density) wages. Import and export exposure generated following Dauth et al. 2014). Group-exposure interactions are import exposure interacted with group effects and export exposure interacted with group effects. Dependent variable in (4) is the predicted trade exposure effect from (3). Standard errors in parentheses. $^+$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
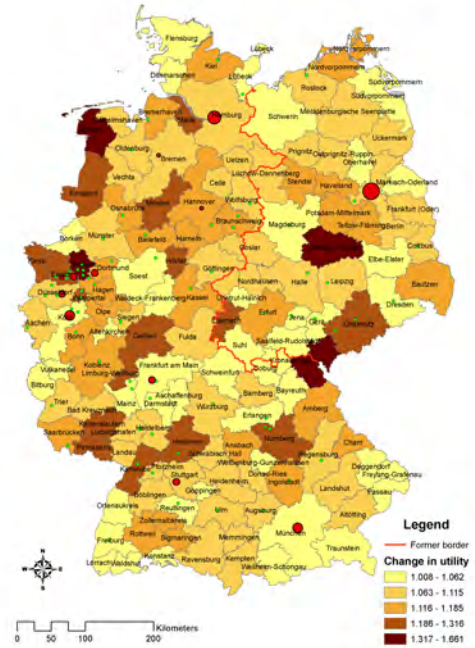
Figure A2: Counterfactuals: Trade shocks
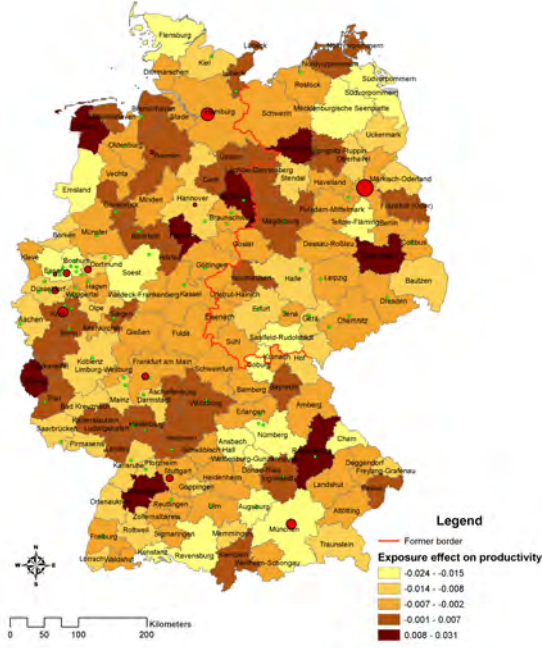
(a) Exogenous effect on productivity ψ_i

(b) Effect on average wage
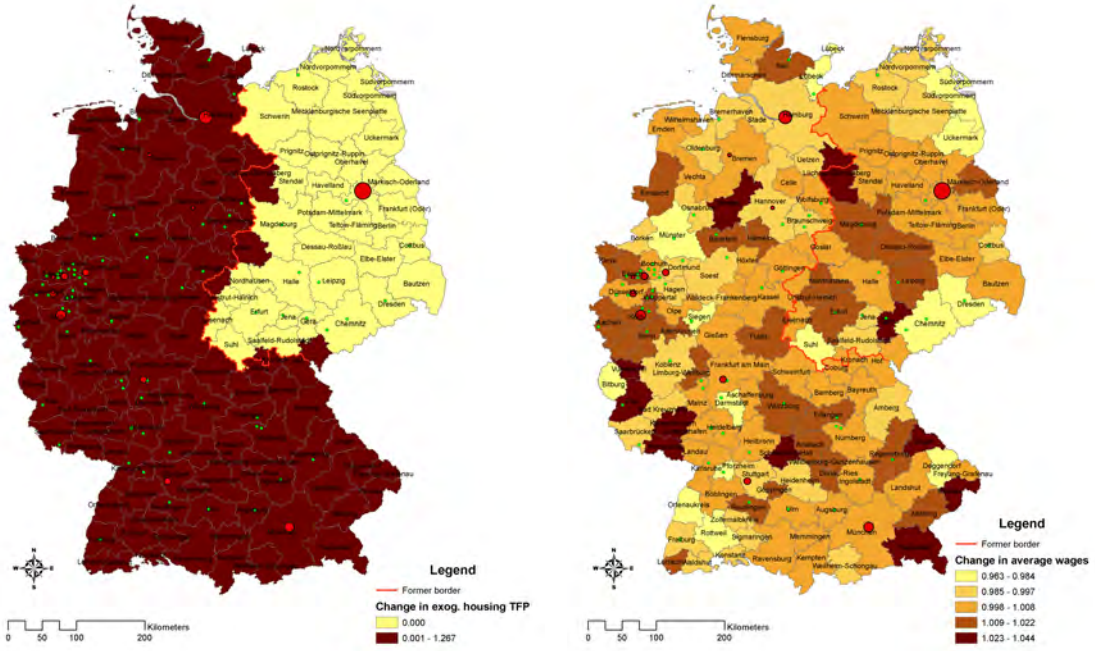
(c) Effect on housing costs

(d) Average effect on utility (at origin)

Note: Illustrations complement the discussion of model-based counterfactuals discussed in Section H.1.
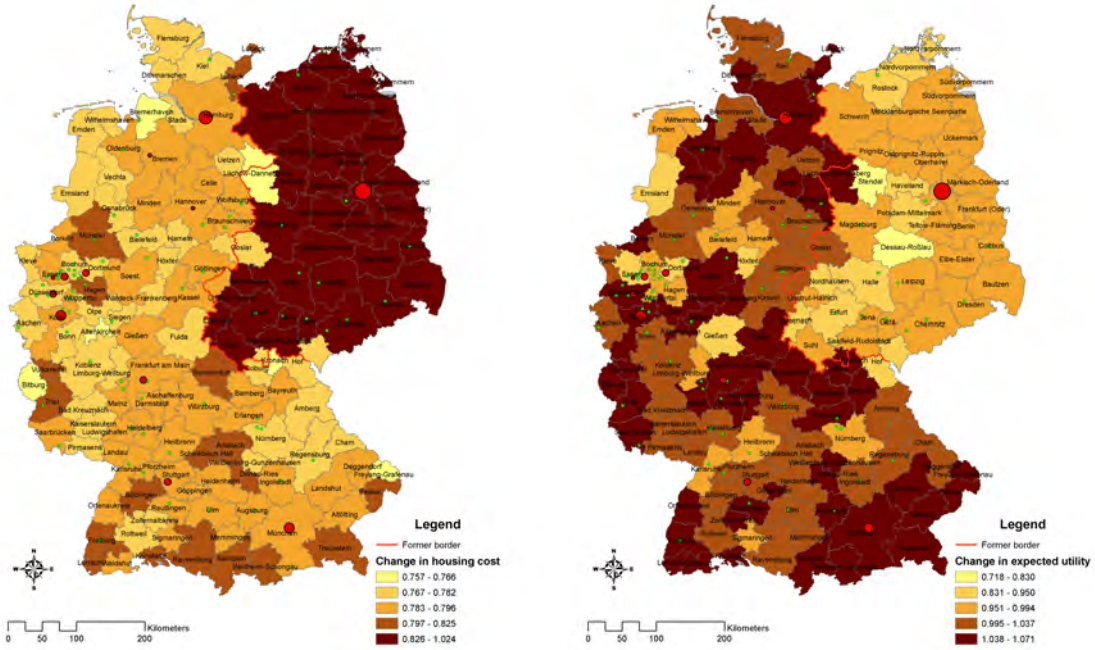
P.2 Land use regulations

In this section, we map the distribution of the exogenous shock on housing TFP and the effects on endogenous variables wages, housing costs, and utility based on the model-based counterfactuals discussed in Section H.2.

Figure A3: Counterfactuals: Land use regulations

(a) Exogenous effect on housing productivity η_i

(b) Effect on average wage

(c) Effect on housing costs

(d) Average effect on utility (at origin)

Note: Illustrations complement the discussion of model-based counterfactuals discussed in Section H.2
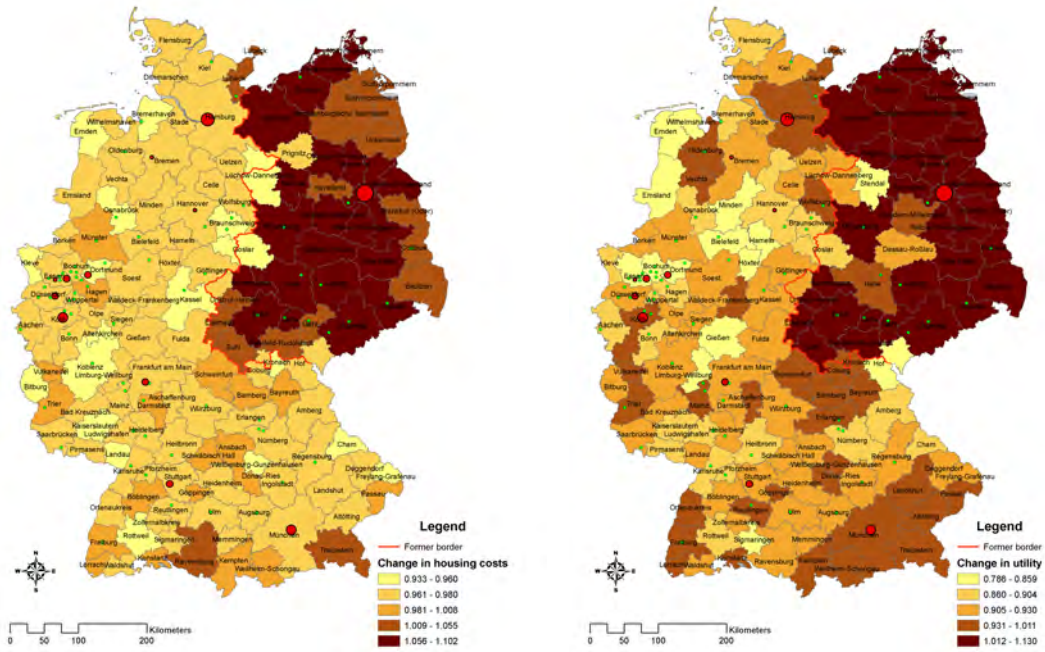
P.3 Regional transfers

In this section, we map the distribution of the per capita and year regional transfers implied by the policy under consideration and its effects on the endogenous variables wages, housing costs, and utility based on the model-based counterfactuals discussed in Section H.2.

Figure A4: Counterfactuals: Regional transfers
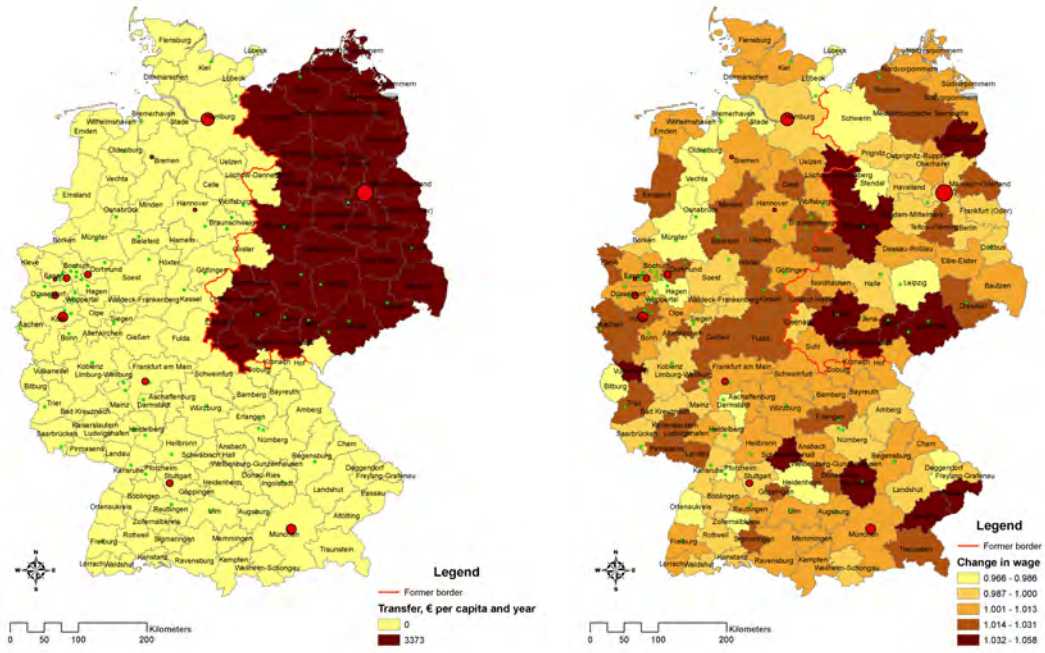
(a) Regional transfer

(b) Effect on average wage

(c) Effect on housing costs

(d) Average effect on utility (at origin)

Note: Illustrations complement the discussion of model-based counterfactuals discussed in Section P.3.

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