Essays in Regional and Labor Economics

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Introduction

Over the past decades, skilled and unskilled households in Western economies have been making increasingly different location choices. College graduates cluster in dense, urban regions to a considerably larger extent than high school graduates.[1] Where a person lives determines the labor market she competes in, the prices she pays as well as the non-pecuniary amenities she experiences. Since diverging location choices might have profound implications for welfare and inequality across skill groups, the topic has attracted growing attention in the urban economics literature (see Diamond and Gaubert (2022) for an overview). The increase in geographic sorting has been linked to a range of economic trends, including growing national and regional wage inequality and widening geographic dispersion in housing costs (Moretti, 2012). There is, however, little consensus on the interplay of the increasing trends in inequality – coined the “Great Divergence” by Moretti (2012) – owing to the empirical challenge of isolating different mechanisms that interact in spatial equilibrium.

This thesis tries to make progress in understanding the driving forces behind the diverging location choices of different groups of workers and their implications for regional disparities, policies and welfare. It consists of three self-contained essays that investigate the causes and consequences of geographic worker sorting using highly disaggregated microdata for Germany. I focus on sorting by education level, and more specifically on the location choices of two worker groups: workers with and without a university degree.[2] Chapter 1 examines to what extent regional disparities in housing costs drive geographic worker sorting by skill. It further analyzes how place-based policies optimally respond to the observed trends. Chapters 2 and 3 investigate the effects of sorting by skill and demographics on regional wage disparities.[3]

[1]For empirical evidence see e.g. Diamond (2016), Diamond and Gaubert (2022) and Giannone (forthcoming) who document an increase in geographic skill sorting in the US, while Figure 1.2 of this thesis shows an increase in geographic skill sorting in Germany.

[2]I thereby follow previous work such as Moretti (2013), Diamond (2016), Diamond and Gaubert (2022) and Giannone (forthcoming).

[3]Note that parts of Chapters 2 and 3 are published as working paper (cf. Furbach, 2023).

In Chapter 1, I study to what extent regional divergence in housing costs contributes to increases in geographic worker sorting.[4] Since housing is a necessity, workers with lower skills (and therefore lower incomes) suffer more from high housing costs, so they tend to avoid expensive regions. Higher skilled workers, on the other hand, spend a smaller share of their income on housing, which makes them less sensitive to differences in housing costs. Consequently, they sort into more expensive urban regions. A large degree of sorting, in turn, amplifies house price differences in large cities as compared to rural areas.

To analyze the mechanism, I use an exogenous shock that has increased housing costs to a larger extent in urban than in rural areas: The national rise in the relative supply of workers with a university degree in Germany has increased the demand for housing. It thereby put upward pressure on house prices that was more pronounced in skill-intensive regions. With the help of a spatial general equilibrium model, I estimate whether high school graduates avoided increasingly expensive regions to a larger extent than college graduates. My findings suggest that the rise in the national relative supply of high skilled workers from 2007 to 2017 can explain 3% of the increase in spatial skill sorting. It accounts for 11% of the regional dispersion in house price increases, while roughly one third of the effect is due to the non-homotheticity of preferences. The national rise in the skill share had small welfare effects on both worker types. Because workers with lower incomes suffered more from increases in housing costs, welfare inequality between low and high skilled workers slightly increased.

My work contrasts vast literature in urban economics that estimates spatial general equilibrium models assuming constant housing expenditure shares, including several studies that investigate the drivers of geographic worker sorting (see e.g. Eeckhout et al., 2014; Diamond, 2016; Rubinton, forthcoming). Using large-scale survey data of German households, I document that low income households spend a significantly larger share of their income on

[4]There is recent empirical literature describing a reversal in the trend of growing regional house price dispersion due to the COVID-19 pandemic: The increase in working from home led some workers to move into distant suburbs. As a consequence, house prices in the periphery have increased relative to urban centers (Delventhal et al., 2022 and Gupta et al., 2022). It is, however, unclear whether firms will maintain remote work options in the long-run and whether employees will continue to use them to the extent they did during the pandemic.

housing.

I next ask how a social planner optimally responds to the observed changes in skill sorting. I assume a social planner who chooses place-based policies in the form of regional skill-specific transfers that affect location choices. I find that the observed degree of skill sorting was not significantly different from the optimal allocation in 2007, while skill sorting was larger than optimal in 2017. Because college graduates, by consuming more housing, generate stronger congestion forces, it is optimal to reallocate them to a larger extent toward rural areas. By analyzing how place-based policies optimally respond to the observed trends, I contribute to emerging literature that studies optimal transfers in the presence of externalities (Rossi-Hansberg et al., 2019; Fajgelbaum and Gaubert, 2020). In contrast to existing studies, I take into account that workers with lower incomes spend a larger expenditure share on housing, making them suffer more from externalities on the housing market.

Chapters 2 and 3 analyze the effect of geographic worker sorting by demographics and skill on the urban wage premium. The main contribution is to study not only differences in productivity but to analyze variation in wages stemming from firms having different degrees of labor market power over different groups of workers. Chapter 2 provides evidence that firms have more labor market power over older and lower educated workers. Chapter 3 finds that these differences can explain a substantial part of spatial wage disparities. The results obtained in Chapter 2 serve as the main parameters that calibrate the spatial general equilibrium model estimated in Chapter 3.

The key parameters calibrated in Chapter 2 capture the degree of labor market power firms have over different groups of workers. I measure labor market power by estimating the sensitivity of worker turnover to the wage paid. Utilizing high-quality matched employer-employee data from German social security records[5], I identify age-specific labor supply elasticities by comparing older with younger workers of the same gender and within the same industry and region. My findings suggest a strong role of demographics in determining the degree of labor market power enjoyed by firms. The chapter thereby highlights an often overlooked dimension of heterogeneity

[5]the Sample of Integrated Labor Market Biographies provided by the federal employment agency

in labor market power. While the literature has studied several dimensions of heterogeneity, this is the first work, to the best of my knowledge, that estimates differences in labor market power over demographic and skill groups.[6]

Chapter 3 provides evidence of the importance of differences in labor market power for spatial wage inequality. Since older and lower skilled workers value rural relative to urban amenities more than younger and higher skilled workers, the share of workers with low labor supply elasticities is larger in rural areas. As a consequence, firms have on average more labor market power in rural areas which gives rise to an urban wage premium. The paper brings a new perspective to a large strand of literature that studies the role of sorting in explaining the urban wage premium (see Diamond and Gaubert (2022) for an overview). While existing literature has focused on the sorting of workers by productivity, I estimate the effect of differences in labor market power that firms have over different groups of workers. I find that differences in labor market power across space resulting from geographic worker sorting by age and demographics can explain 10% of the urban wage premium. However, after baby boomers retire, we can expect little changes in regional wage disparities.

[6] There is literature that finds firms to have more labor market power over migrants (Hirsch and Jahn, 2015), females (Barth and Dale-Olsen, 2009; Hirsch et al., 2010) and workers in rural labor markets (Hirsch et al., 2022). Bamford (2021) explains higher labor market power in rural areas with lower competition among potential employers due to a smaller number of firms.

CHAPTER 1

Non-homothetic Housing Demand and Geographic Worker Sorting

Chapter Abstract

Housing expenditure shares decline with income. A household's income determines its sensitivity to housing costs and drives its location decision. Has spatial skill sorting increased because low income households are avoiding increasingly expensive regions? I augment a standard quantitative spatial model with flexible non-homothetic preferences. I apply the model to estimate the effect of the national increase in the relative supply of high skilled workers that put upward pressure on housing costs in skill-intensive cities. My model attributes 11% of the observed regional differences in house price increases from 2007 to 2017 in Germany to the growth in the national share of high skilled workers. It can further explain 3% of the increase in spatial sorting. The national rise in the skill share has decreased welfare of low skilled workers by 0.9% and welfare of high skilled workers by 0.8%. From a social planner perspective, it would be optimal to decrease congestion forces by setting incentives for all workers to move toward less expensive regions, but to a larger extent for high skilled workers.

1.1 Introduction

Western economies are experiencing a housing crisis unlike anything we have seen for decades. About half of Americans (49%) say the availability of affordable housing in their local community is a major problem (Schaeffer, 2022). At the same time, real house prices in the US have risen by 35% from 2010 to 2020. House price increases are sizable also in other Western economies: In Germany, house prices in 2020 were 47% higher than in 2010 (OECD, 2022). These developments are more and more seen as a driver of increasing economic inequality. The growing cost burden is not equally distributed across households since poorer households spend a significantly larger share of their income on housing. However, we know very little about how hard the lack of affordable housing hits households across the income distribution, nor do we know much about how it affects location decisions.

The fact that workers with lower incomes suffer more from increasing housing costs provides one possible explanation for the trends in location choices observed over the past decades: College graduates have clustered in high-wage, high-cost cities while high school graduates avoid increasingly expensive cities. The increase in sorting, in turn, amplifies house price increases in large cities as compared to rural areas. To analyze this mechanism, I use the national increase in the relative supply of workers with a college degree. By increasing the demand for housing, it puts upward pressure on house prices that is more pronounced in skill-intensive regions. I study in how far the national rise in the skill share can explain the simultaneous increase in spatial skill sorting and regional differences in housing costs.

I start by estimating the degree of non-homotheticity using large-scale survey data of German households. My results establish that non-homotheticity in housing demand is both econometrically and economically significant. I set up a spatial general equilibrium model of non-homothetic housing demand to estimate the effect of the national rise in the relative supply of college graduates. Calibrating the model with the estimated preference parameters, I find that the rising skill share explains 3% of the increase in spatial sorting by skill and 11% of the regional differences in house price increases from 2007 to 2017 in Germany. With homothetic preferences, a national increase in the supply of high skilled workers does not change skill sorting which implies that it can explain only 7% of the regional dispersion in house price increases. The rise in the skill share has decreased welfare of low skilled workers by 0.9% and welfare of high skilled workers by 0.8%.

I next ask how a social planner optimally responds to the observed changes in skill sorting. I analyze the optimal allocation in 2007 and 2017 using a utilitarian welfare function. I choose to study the allocation that equally benefits all worker types. The social planner maximizes welfare taking into account redistribution and efficiency considerations. To do so, she chooses regional type-specific taxes and transfers that set incentives for workers to move across space. I find that the observed degree of skill sorting was not different from the optimal allocation in 2007, while skill sorting was larger than optimal in 2017. From a social planner perspective, it would be optimal to set incentives for all workers to move toward rural areas, but to a larger extent for high skilled workers. Moving from the observed to the optimal allocation implies welfare gains of 0.4% in 2007 and 0.5% in 2017.

I arrive at these conclusions by studying sorting in a spatial general equilibrium model with heterogeneous workers that have non-homothetic preferences. I include two worker types: high school graduates and college graduates. In my model, heterogeneous workers with Generalized Elasticity of Substitution (GES) preferences trade off wages, housing costs and regional amenities when making their location decision. Locations differ exogenously in terms of housing fundamentals, group-specific productivity and group-specific amenities. I further include heterogeneous preference shocks for locations that act as a form of migration costs. Identical firms combine labor from different worker groups to produce a final good that is traded between regions at zero cost.

The quantification follows the basic steps known from the literature on quantitative spatial models (see Redding and Rossi-Hansberg (2017) for an overview). First, I use observed data and the structure of the model to calibrate the key structural parameters. I estimate non-homothetic preferences over housing and non-housing consumption utilizing large-scale consumption microdata from the German Socio-Economic Panel (GSOEP). I start by linearizing the relationship between the housing expenditure share and total expenditure derived from the model. From the reduced-form estimation of this first-order approximation, I obtain parameters that are directly interpretable as elasticities and therefore comparable to estimates from the literature. Guided by the structure of the model, I control for local house prices since households' sorting decisions introduce a positive correlation between prices and incomes at the regional level (Albouy et al., 2016 and Finlay and Williams, forthcoming). I find that a 100% increase in total expenditure causes a 27% decrease in the housing expenditure share. My estimates are well in line with those found in comparable studies (see Finlay and Williams (forthcoming) for an overview). For the calibration of the model parameters, I estimate the non-linear relation between the housing expenditure share, total expenditure and house prices derived from the model directly by Generalized Method of Moments (GMM). I reject two alternative preferences used in the literature: Cobb-Douglas and a unit housing requirement.

In the second step of the quantification, I use observed data, the structure of the model, and the structural parameters to invert the structural productivity, housing and amenity fundamentals. For the model inversion, I leverage on matched employer-employee data from German social security records. In particular, for every year, I observe the local labor market in which individuals work (Kosfeld and Werner, 2012), the nominal wage and a range of individual-level characteristics. I use this information to construct a regional wage measure that is purged from differences in observable worker characteristics between regions. Aggregation of the microdata yields employment and average wage by region and worker group for 2007 and 2017. To these data, I merge a regional mix-adjusted property price index, which is generated from property microdata from the largest German listing website (Ahlfeldt et al., 2022b).

The model is quantified to match the observed data on house prices, skill-specific wages and skill-specific employment on the regional level. It is further calibrated to be consistent with the empirically documented estimates on the non-homotheticity of preferences. I use the model to quantify the importance of accounting for non-homothetic preferences when analyzing geographic worker sorting. To do so, I estimate the effect of the rise in housing congestion resulting from the national increase in the relative supply of college graduates. The size of the shock amounts to an increase in the national share of high skilled workers from 16% in 2007 to 22% in 2017. In the model with non-homothetic preferences, the shock leads to intensified geographic worker sorting since low skilled workers are hit harder by increases in housing costs that are more pronounced in skill-intensive regions. The increase in sorting, in turn, amplifies house price increases in large cities as compared to rural areas. The model allows for exogenous changes in productivity, housing and amenity fundamentals. Feeding the national shock of an increase in the skill share into the model, the model accounts for 11% of the regional dispersion in house price increases. Roughly one third of the effect is due to the non-homotheticity of preferences. Non-homothetic preferences can explain 3% of the observed change in skill sorting. I find that the shock has decreased welfare of low skilled workers by 0.9% and welfare of high skilled workers by 0.8%.

The experiment explores the importance of allowing for non-homothetic preferences when analyzing sorting in a spatial equilibrium model. I next ask: What is the optimal degree of skill sorting? There are two reasons why the social planner allocation differs from the observed equilibrium. First, because wages are on average lower, marginal utilities of tradable good consumption are larger in rural areas. The social planner increases welfare by redistributing from urban to rural regions which sets incentives for workers to move across space. Secondly, since congestion forces are not taken into account by workers when choosing their place of residence, there is space for welfare improvement by setting incentives to move toward rural areas. Non-homothetic preferences affect the optimal allocation in several ways. Since lower skilled workers have a larger housing expenditure share than with homothetic preferences, they demand more housing. This implies that they generate stronger congestion forces than with homothetic preferences, while at the same time being more sensitive to housing congestion. Workers with higher skills, on the other hand, generate lower congestion forces than with homothetic preferences, while being less sensitive to housing congestion. Furthermore, by changing the marginal utililities of tradable good consumption, non-homothetic preferences affect the optimal degree of redistribution between regions.

I use the model to compute the optimal allocation which provides insights into the welfare implications of spatial skill sorting. I solve the problem of a social planner who maximizes a utilitarian welfare function taking as given workers' location choices as well as resource constraints on housing and tradables. To do so, she chooses transfers between locations and worker types which I characterize. Welfare weights are calibrated such that both worker types experience the same welfare gain. While the observed degree of skill sorting was not different from the optimal allocation in 2007, skill sorting was larger than optimal in 2017. Since high skilled workers, by consuming more housing than low skilled workers, generate larger congestion forces, it is optimal to reallocate them to a larger extent toward regions with less congested housing markets. Furthermore, since the urban wage premium is larger for high skilled workers, spatial differences in marginal utilities of tradable good consumption are larger for high skilled than for low skilled workers. It is therefore optimal to redistribute consumption goods between regions to a larger extent for college graduates than for high school graduates. The smaller degree of agglomeration and skill sorting in the optimal allocation imply that house prices are less dispersed. My findings indicate that moving from the observed to the optimal allocation implies welfare gains of 0.4% in 2007 and 0.5% in 2017.

This chapter is related to several strands of literature. One strand aims at explaining the diverging location choices between skilled and unskilled households. While some studies have stressed the role of endogenous amenities (Diamond, 2016) or the role of technology in generating skill-biased wage growth in certain locations (Eckert et al., 2020; Giannone, forthcoming; Rubinton, forthcoming), few studies show that non-homothetic housing demand significantly affects spatial sorting. Ganong and Shoag (2017) connect changes in housing supply regulations to slowing regional income convergence. In contrast to Ganong and Shoag (2017) who estimate the effect of location-specific shocks, a small number of papers show that non-homotheticities matter in the presence of national shocks. Finlay and Williams (forthcoming) find that skill-biased technological change on the national level has intensified skill sorting since it made lower skilled workers relatively more sensitive to housing costs. In a similar manner, Couture et al. (forthcoming) find that rising income inequality has increased within-city sorting and led to a gentrification of downtowns that made poorer households significantly worse off. Gyourko et al. (2013) show that the increase in spatial skill sorting can be explained by an increasing number of high skilled households nationally combined with an inelastic supply of land in superstar cities. I show that the national increase in the number of high skilled workers leads to an increase in spatial sorting even with uniform housing supply elasticities.

In the second part of my analysis, I take one step further and ask how non-homothetic preferences shape the optimal allocation and the taxes and transfers that could implement it. I thereby complement a large literature on the extent of spatial misallocation and the role that transfer and taxation policies play (Albouy, 2009; Fajgelbaum et al., 2018; Colas and Hutchinson, 2021; Ossa, forthcoming). Rather than evaluating exogenous policies, I derive the optimal allocation in a quantitative spatial model with local congestion forces. Since my model is flexible enough to capture any degree of non-homotheticity, my results generalize those of Fajgelbaum and Gaubert (2020) who assume Cobb-Douglas preferences. Including skill-specific productivity and amenity spillovers, Fajgelbaum and Gaubert (2020) find that the US economy would benefit from a smaller degree of skill sorting. According to the results of Rossi-Hansberg et al. (2019) on the other hand, it would be optimal to take advantage of scarce cognitive non-routine workers by clustering them in small cognitive hubs to maximize positive production externalities. My results are in line with Fajgelbaum and Gaubert (2020) and propose that spatial skill sorting is larger than optimal.

This chapter is further related to literature estimating non-homotheticities in housing demand. At the level of cities, a common assumption is that preferences are Cobb-Douglas and therefore homothetic (see e.g. Eeckhout et al., 2014; Diamond, 2016; Rossi-Hansberg et al., 2019; Fajgelbaum and Gaubert, 2020). This assumption is often justified by the fact that housing expenditure shares vary little across cities with very different income levels (Davis and Ortalo-Magné, 2011). My results are in line with Albouy et al. (2016) and Finlay and Williams (forthcoming) who offer an alternative explanation for the similarity of housing expenditure shares across cities: offsetting price and income effects. While Albouy et al. (2016) rely on city-level variations in incomes, prices, and rental expenditure, I follow Finlay and Williams (forthcoming) and use consumption microdata. I find demand elasticities that are in line with previous studies (see Finlay and Williams (forthcoming) for an overview).

The remainder of the chapter is structured as follows. Section 1.2 presents stylized evidence that informs my modeling choices. Section 1.3 introduces a model with heterogeneous workers that have non-homothetic preferences and Section 1.4 calibrates a quantitative version of this model. Section 1.5 uses the calibrated model to quantify the role of non-homothetic preferences when the national supply of different worker types changes. It further analyzes optimal regional taxes and transfers. Section 1.6 concludes.

1.2 Motivating facts

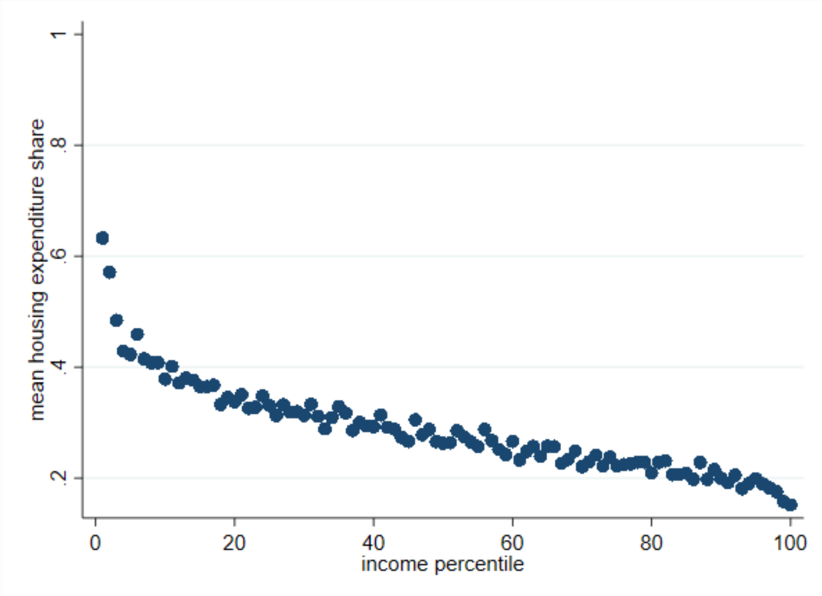
To motivate the relevance of non-homothetic preferences in the context of spatial skill sorting, I present some stylized facts using data I describe in Section 1.4.1. I start by plotting the housing expenditure share for each percentile of the income distribution in Figure 1.1. It can be seen that housing expenditure shares are far from constant: Moving from the 10th percentile of the income distribution to the 90th percentile implies a decrease in the housing expenditure share from 38% to 21%.[1] The result is robust to controlling for household size. In Section 1.4.2, I estimate the degree of non-homotheticity and I reject the null hypothesis of constant housing expenditure shares.

Non-homothetic preferences could potentially drive the patterns observed in the data and illustrated in Figure 1.2. The upper plots show that from 2007 to 2017, house prices have increased significantly more in large labor markets. I find that the elasticity of house prices with respect to employment has increased by almost 43%. At the same time, skill sorting has intensified since high skilled workers are increasingly attracted by large regions, even to a larger extent than low skilled workers. The semi-elasticity of the share of high skilled workers with respect to city size has increased by 44%.

In the following, I study a mechanism that links the three stylized facts. It can explain the simultaneous increase in regional house price differences and spatial skill sorting with the help of non-homothetic preferences: A national increase in the relative supply of high skilled workers has increased the demand for housing. The shock has put upward pressure on house

[1] A comparison to data 30 years ago reveals that the decrease in housing affordability is mainly a problem of low income households: The housing expenditure share has increased significantly more for low income than for high income households (see Figure 1.A.1).

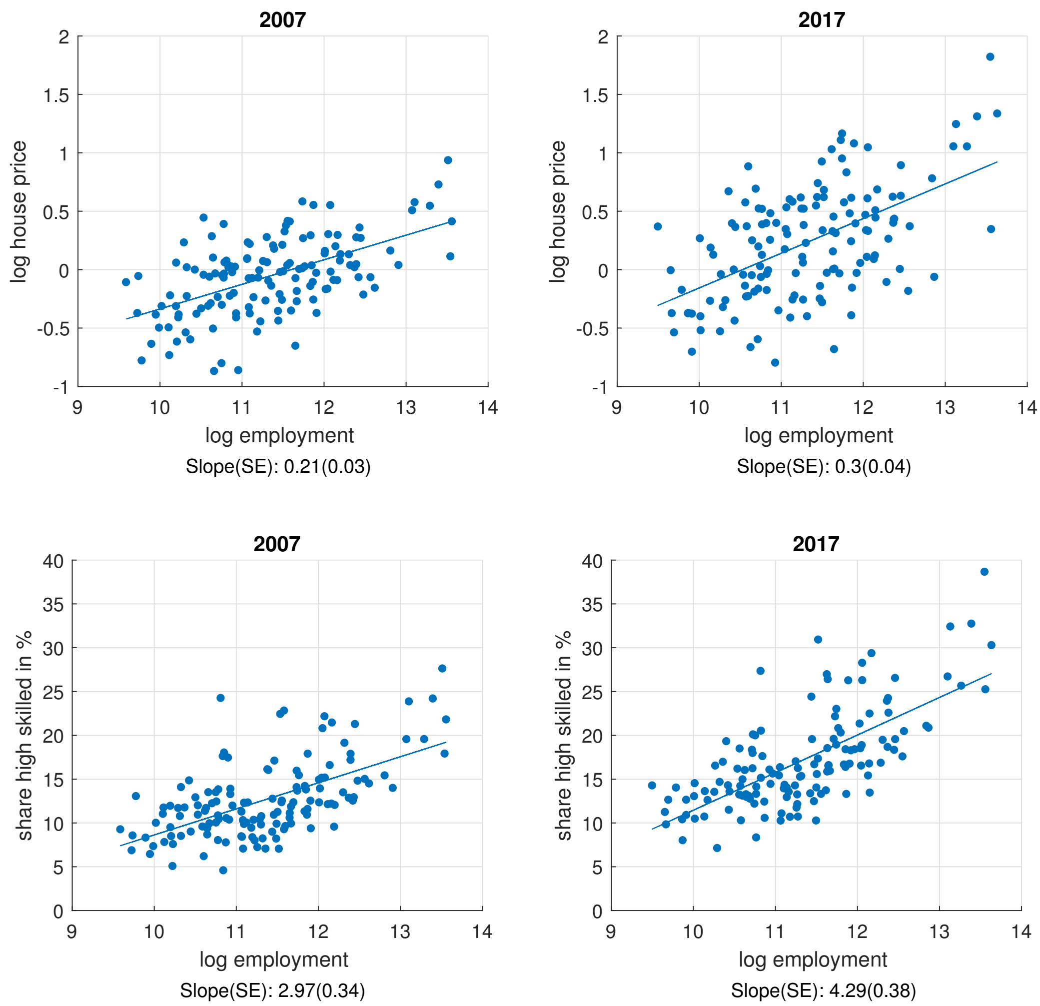
Figure 1.1: Housing expenditure shares and income



Note: Housing expenditure share is defined as housing expenditure (including heating and electricity) divided by total net income. The plot is based on household data from 2017. Number of observations: 6648

prices that was more pronounced in skill-intensive regions. Due to lower housing expenditure shares, workers with higher incomes suffered less from increasing housing costs in these regions. Non-homothetic preferences in combination with the national increase in high skilled workers can explain why skilled households have clustered in large labor markets while unskilled workers increasingly avoided these regions. The increase in sorting, in turn, amplified house price increases in large cities as compared to rural areas.

Figure 1.2: Geographic sorting and house prices



Note: Unit of observation is 141 labor market areas as defined by Kosfeld and Werner (2012). House prices are relative to the national mean in 2007. Share high skilled refers to the number of full-time employed workers with a university degree relative to all full-time employed workers.

1.3 A quantitative spatial model with non-homothetic preferences

1.3.1 Competitive allocation

In this section, I develop a spatial general equilibrium model with heterogeneous workers that have non-homothetic preferences. I consider an economy that is populated by $L_t = \sum_k L_{kt}$ workers in year t who I categorize into groups indexed by k. Heterogeneous workers choose a region i taking as given the location decision of all other individuals. Local labor markets vary exogenously in their productivity, amenities, and housing supply. I include worker-specific preference shocks for locations that act as a form of migration costs. Conditional on their labor market, workers maximize utility over consumption of housing and tradable goods. I incorporate regional congestion forces by assuming an inelastic supply of housing. Homogeneous firms employ different worker types to produce goods that are traded at zero cost.

Workers

Preferences of a worker n in year t working in region i and belonging to group k are defined over freely-tradable homogeneous goods c_{ikt}, housing h_{ikt}, regional amenities E_{ikt} and the idiosyncratic amenity shock ϵ_{int}. I assume GES preferences that take the following form

$$u_{int} = \left(\gamma c_{ikt}^{1-\frac{1}{\rho}} + (1-\gamma) h_{ikt}^{1-\frac{\eta}{\rho}}\right)^{\frac{\rho}{\rho-1}} E_{ikt}\epsilon_{int} \tag{1.1}$$

with $\gamma > 0$, $0 < \rho < 1$ and $\eta > \rho$. ρ is the elasticity of substitution and η captures the degree of non-homotheticity. GES preferences nest the specifications commonly used in the spatial literature. If $\rho \to 1$ and $\eta = 1$, I obtain Cobb-Douglas preferences where γ is the expenditure share on tradables.[2] In the opposite case, when $\eta \to \infty$, I get a unit housing requirement which is a very extreme form of non-homotheticity often assumed in the literature. GES preferences, in contrast, can accommodate any degree of non-homotheticity. In the empirically relevant case, $\eta > 1$ and expenditure shares on housing decrease with income.

Conditional on working in region i, a type-k worker solves the following

[2]Note that if $\eta = 1$ only, I get constant elasticity of substitution preferences.

problem:

$$\begin{aligned} v_{ikt} &= \max_{c_{ikt},h_{ikt}} \left(\gamma c_{ikt}^{1-\frac{1}{\rho}} + (1-\gamma) h_{ikt}^{1-\frac{\eta}{\rho}} \right)^{\frac{\rho}{\rho-1}} E_{ikt} \\ s.t. & \\ c_{ikt} + p_{it} h_{ikt} &= w_{ikt} + \Pi_{ikt} + t_{ikt} \end{aligned} \tag{1.2}$$

where p_{it} is the price of housing, w_{ikt} is the wage and t_{ikt} is the net government transfer to a type-k worker in region i and year t. The tradable good is chosen to be the numéraire. Π_{ikt} is the return on a regional portfolio of housing that equals individual housing expenditure:

$$\Pi_{ikt} = p_{it} h_{ikt}. \tag{1.3}$$

I assume that ϵ_{int} is drawn from a type-1 extreme value distribution with shape parameter ψ that reflects the extent of preference heterogeneity across regions. If the variation in regional amenity draws is large, workers show little sensitivity to differences in wages, house prices and exogenous amenities, which implies low geographic mobility. The distributional assumption on region-specific amenity draws implies closed-form expressions for the number of workers in each region

$$L_{ikt} = \frac{v_{ikt}^{\frac{1}{\psi}}}{\sum_i v_{ikt}^{\frac{1}{\psi}}} L_{kt} \tag{1.4}$$

where $L_{kt} = \sum_i L_{ikt}$ is the total number of type-k workers.

Firms

Identical firms combine labor from different worker groups to produce the freely-traded final good. I assume a linear production function with group- and location-specific productivity shifters A_{ikt}. Firm-level production functions translate directly to city-level production since firms face constant returns to scale and share an identical production technology. The regional-level production function is given by

$$Y_{it} = \sum_k A_{ikt} L_{ikt}. \tag{1.5}$$

Firms pay wages that are equal to the marginal product of labor

$$w_{ikt} = A_{ikt}. \tag{1.6}$$

The regional supply of housing H_{it} is determined by an exogenous part T_{it} that captures the availability of land and an endogenous part that depends on total city population $L_{it} = \sum_k L_{ikt}$:

$$H_{it} = T_{it} L_{it}^{\gamma_H} \tag{1.7}$$

where γ_H is the housing supply elasticity.

Equilibrium

In equilibrium, the market for tradable goods clears:

$$\sum_i Y_{it} = \sum_i \sum_k L_{ikt} c_{ikt} \tag{1.8}$$

which follows from the household budget constraint in equation (1.2) combined with a balanced government budget $\sum_i \sum_k L_{ikt} t_{ikt} = 0$. Housing market clearing requires

$$H_{it} = \sum_k L_{ikt} h_{ikt} \tag{1.9}$$

where housing demand is given by the combined first-order conditions of the household maximization problem

$$h_{ikt} = \left(\frac{1}{p_{it}} \frac{1-\gamma}{\gamma} \frac{\rho - \eta}{\rho - 1} \right)^{\frac{\rho}{\eta}} (c_{ikt})^{\frac{1}{\eta}}. \tag{1.10}$$

Labor markets clear when equation (1.4) and equation (1.6) hold.

Thus, for given parameters γ, ρ, η, ψ and γ_H, location-specific fundamentals A_{ikt}, T_{it}, E_{ikt} and taxes t_{ikt}, an equilibrium is a vector of L_{ikt}, w_{ikt}, c_{ikt},

h_{ikt}, Π_{ikt}, p_{it}, H_{it} and Y_{it} satisfying equations (1.2) to (1.10).[3]

Potential mechanisms

In a quantitative spatial model as laid out in this section, a number of different shocks could rationalize the patterns observed in the data and presented in Section 1.2. With homothetic preferences, a simultaneous increase in both spatial skill sorting and regional house price differences could result from shocks to A_{ikt} or E_{ikt}, i.e. from region-specific shocks to productivity or amenity fundamentals that differ across skill types. One example would be skill-biased technological change with differential effects across regions depending on their industry composition. If high skilled workers become more productive mainly in dense regions, house prices increase in these regions since more high skilled workers move there. An alternative explanation would be regional shocks that are symmetric across skill types in combination with asymmetric spillovers. Consider the case in which all workers become more productive in denser regions. Such a productivity shock would increase the spatial concentration of population. If high skilled workers benefit more from knowledge spillovers in dense cities, we would observe an increase in both house prices and geographic skill sorting. A large literature combines both asymmetric spillovers with asymmetric region-specific shocks to fundamentals such that spillovers amplify the effects of shocks to regional fundamentals (see e.g. Diamond, 2016 and Giannone, forthcoming). Another explanation is that agglomeration spillovers themselves have changed over time. Baum-Snow and Pavan (2013) argue that agglomeration forces of high skilled workers have become stronger relative to those of low skilled workers which led to an increase in spatial skill sorting.

With non-homothetic preferences, a number of additional shocks could rationalize the increase in both regional house price differences and spatial skill sorting. Even in the absence of spillovers, productivity and amenity shocks that are common across regions might lead to a change in spatial skill sorting. Finlay and Williams (forthcoming) model skill-biased technological

[3] When estimating the model, I impose $t_{ikt} = 0 \ \forall \ i, k, t$ both in the observed and counterfactual scenario. In this case, equation (1.8) follows from the household budget constraint (equation (1.2)) in combination with housing returns (eqution (1.3)) and is therefore redundant.

change as a national shock to productivity fundamentals of high skilled relative to low skilled workers. Assuming non-homothetic preferences, they find that skill-biased technological change can explain 23% of the increase in skill sorting in the US since 1980. Gyourko et al. (2013) argue that the simultaneous increase in geographic skill sorting and spatial house price differences can be explained by an inelastic supply of land in superstar cities combined with an increasing number of high income households nationally. In the following, I show that the national increase in the relative supply of high skilled workers leads to an increase in spatial sorting even with uniform housing supply elasticities γ_h.

1.3.2 The social planner's problem

In this section, I characterize the optimal allocation and the taxes and transfers that implement it. There are two reasons why the social planner allocation differs from the observed equilibrium. First, the decentralized world is inefficient due to congestion forces on regional housing markets. The fact that housing supply is inelastic ($\gamma_h < \infty$) implies an externality: Workers do not generate the same degree of congestion in all regions which is not taken into account when choosing a place of residence. Thus, there is space for welfare improvement by reallocating workers across space (Fajgelbaum and Gaubert, 2020). Second, marginal utilities of tradable good consumption are not constant across regions. The social planner increases welfare by redistributing toward regions with low marginal utilities of consumption.

My aim is to contrast the decentralized allocation with the solution to the planner's problem. I solve the problem of a social planner who takes as given that workers can freely move across labor markets. Under this assumption, expected utility of a type-k worker in year t is given by

$$u_{kt}^{exp} = \psi \log\left(\sum_i e^{\frac{\frac{\rho}{\rho-1}\log\left(\gamma c_{ikt}^{1-\frac{1}{\rho}} + (1-\gamma) h_{ikt}^{1-\frac{\eta}{\rho}}\right) + \log E_{ikt}}{\psi}}\right). \tag{1.11}$$

Then, if ω_{kt} denotes the welfare weight for skill type k in year t, I can postulate the generalized social welfare function

$$\mathcal{W} = \sum_k \omega_{kt} \psi \log\left(\sum_i e^{\frac{\frac{\rho}{\rho-1}\log\left(\gamma c_{ikt}^{1-\frac{1}{\rho}} + (1-\gamma) h_{ikt}^{1-\frac{\eta}{\rho}}\right) + \log E_{ikt}}{\psi}} \right). \tag{1.12}$$

The planner maximizes the expression in equation (1.12) subject to workers' location choices (equation (1.4)), the resource constraint on housing (equation (1.9)) as well as the resource constraint on tradables (equation (1.8)). I turn next to characterizing the solution to this planning problem.

Competitive equilibria according to the definition in Section 1.3.1 may not correspond to a point on the Pareto frontier due to spatial inefficiencies: Workers do not internalize the impact that their location choice has on other workers in the form of housing congestion. The social planner takes the social costs of additional workers in different regions into account when setting incentives for workers to move between labor markets. In the optimal allocation, the social marginal cost of an additional type-k worker in region i has to equal its social marginal value. More formally, I can express optimal expenditures as

$$\mu_t^Y c_{ikt} + \mu_{it}^h h_{ikt} = w_{ikt} + \widetilde{\Pi}_{ikt} + \lambda_{ikt} \tag{1.13}$$

where μ_t^Y, μ_{it}^h and λ_{ikt} are Lagrange multipliers on the government budget constraint, the resource constraint on housing and the mobility constraint. $\widetilde{\Pi}_{ikt}$ denotes the social marginal value generated in the housing sector:

$$\widetilde{\Pi}_{ikt} = \mu_{it}^h \frac{\partial H_{it}}{\partial L_{ikt}}. \tag{1.14}$$

Thus, the social planner implements transfers according to

$$t_{ikt} = \Phi_{ikt} + \lambda_{ikt} \tag{1.15}$$

where $\Phi_{ikt} = \widetilde{\Pi}_{ikt} - \Pi_{ikt}$ is the wedge between the private and the social marginal value of an extra type-k worker in region i in year t.[4]

The proposition generalizes a key insight in Fajgelbaum and Gaubert

[4]Details on the derivations are given in Section 1.B.

(2020) to an economy with non-homothetic preferences and imperfect worker mobility between regions. As pointed out by Fajgelbaum and Gaubert (2020), the optimal transfers t_{ikt} take care of inefficiencies due to spillovers as well as distributional concerns. In the absence of spillovers, I would still have $t_{ikt} = \lambda_{ikt}$, so that transfers would redistribute according to differences in the marginal utility of consumption, as implied by the second welfare theorem. In Fajgelbaum et al. (2018), workers are perfectly mobile and hold Cobb-Douglas preferences. In this case, λ_{ikt} does not depend on the region. The burden of dealing with spatial inefficiencies falls on the other component of the optimal transfer scheme, corresponding to the first term in equation (1.15).

1.4 Quantifying the model

I calibrate the model to German labor market regions in 2007 and 2017. The quantification of the model consists of two steps that follow the literature on quantitative spatial models (see Redding and Rossi-Hansberg (2017) for an overview). First, I obtain values of the structural parameters. I estimate the preference parameters γ, ρ and η using variables observed in the data and the structure of the model. The housing supply elasticity γ_H and the migration elasticity ψ are taken from the literature. Second, I use data from 2007 and 2017, the calibrated parameter values, and the structure of the model to invert the structural fundamentals A_{ikt}, T_{it} and E_{ikt} for $t = 2007$ and $t = 2017$.

1.4.1 Data

I estimate the model on the level of 141 German labor market regions as defined by Kosfeld and Werner (2012) based on commuting data. The areas are constructed by combining one or more districts with the aim of creating self-contained labor markets. The boundaries of local labor markets are defined such that commuting flows between labor market regions are minimized. I drop all regions in which the number of observations for any worker group is smaller than 20. I end up with a sample of 138 labor markets.

I obtain information on regional employment and wages for different worker groups from the microdata on individual employment histories from the Sample of Integrated Labor Market Biographies (SIAB) provided by the Institute for Employment Research (Antoni et al., 2019). The SIAB is a 2% representative sample of administrative data on all workers who are subject to social security contributions in Germany, excluding self-employed and civil servants. I restrict the sample to full-time workers between 20 and 64 and use the consumer price index from Statistisches Bundesamt (2019) to calculate real wages. In the SIAB data, I only observe wages up to the social security contribution ceiling. To impute top-coded wages for the roughly 5% of observations above the social security contribution ceiling, I use the approach from Dauth and Eppelsheimer (2021).

I split the sample into 2 groups: workers with and workers without a university degree.[5] I aggregate wages to the labor market level by running the following regression for every worker group k and for the years 2007 and 2017 separately:

$$\ln w_{nt}^{raw} = \alpha_{kt} + \beta_{kt} X_{nt} + d_{ikt} + \epsilon_{nt} \tag{1.16}$$

where X_{nt} is a set of observable worker characteristics, d_{ikt} is a group-region dummy, and ϵ_{nt} is an error term.[6] Given the Mincerian regressions, I rescale average wages according to

$$w_{ikt} = \exp\left(\alpha_{kt} + \beta_{kt} \frac{1}{L_{kt}} \sum_{nt \in k} X_{nt} + d_{ikt}\right) \tag{1.17}$$

which represents the average wage of a type-k worker in region i in year t while assuming that workers have otherwise identical characteristics between regions.

I use a house price index from Ahlfeldt et al. (2022b) who utilize data from the FDZ (Forschungsdatenzentrum) Ruhr on real estate offers published on the largest German listing website ImmobilienScout24 with a self-reported market share of about 50% (Klick and Schaffner, 2019). By combining a

[5] Individuals are assigned the highest qualification level that they achieve throughout their working life.

[6] The controls include sex, a dummy that indicates whether a person is German, detailed level of educational attainment, duration of past unemployment periods, and duration of past unemployment periods squared.

hedonic regression approach with recent extensions that treat spatial units as the nucleus of a spatial price gradient, Ahlfeldt et al. (2022b) generate an index that controls for property characteristics and distance from the center of the labor market region.

To calibrate the preference parameters, I use consumption microdata from the GSOEP which is a yearly survey with information on income, expenditure and education of approximately 11000 private households.[7]

Table 1.1: Summary Statistics

	2007		2017	
	mean	sd	mean	sd
Wage low skill	83.17	9.25	94.91	10.09
Wage high skill	148.17	22.42	157.64	21.03
Total employment (in thd)	126.91	142.75	126.13	146.04
Share high skill (in %)	12.62	4.36	17.10	5.57
House purchase price	1	0.34	1.43	0.80

Note: The table shows descriptive statistics for cross-sectional data on the level of 138 labor markets. Wages are gross daily wages, house prices are relative to the national mean in 2007.

1.4.2 Structural parameters

Preference parameters ρ and η

To calibrate the preference parameters of the model, I utilize the household first-order condition as defined in equation (1.10). Defining total expenditure $x_{ikt} \equiv c_{ikt} + p_{it}h_{ikt}$, multiplying with $\frac{p_{it}}{x_{ikt}}$ and substituting for c_{ikt} yields

$$s_{ikt} = \left(\frac{1-\gamma}{\gamma}\frac{\rho-\eta}{\rho-1}\right)^{\frac{\rho}{\eta}} p_{it}^{1-\frac{\rho}{\eta}} x_{ikt}^{-(1-\frac{1}{\eta})} (1-s_{ikt})^{\frac{1}{\eta}} \tag{1.18}$$

[7] I exclude households where the household head is non-employed, doing an apprenticeship, is younger than 18 or older than 64 years, has refugee status or is seeking asylum as well as all households with owner-occupied housing.

where $s_{ikt} \equiv \frac{p_{it} h_{ikt}}{x_{ikt}}$ denotes the housing expenditure share. To estimate this equation, I use the variation across households h. I interpret $\alpha \equiv (\frac{1-\gamma}{\gamma}\frac{\rho-\eta}{\rho-1})^{\frac{\rho}{\eta}}$ as an idiosyncratic shock to a household's taste for housing, so that equation (1.18) becomes

$$s_{ht} = \alpha_{ht} p_{it}^{1-\frac{\rho}{\eta}} x_{ht}^{-(1-\frac{1}{\eta})} (1 - s_{ht})^{\frac{1}{\eta}}. \tag{1.19}$$

I follow Finlay and Williams (forthcoming) and log-linearize equation (1.19) around the mean housing expenditure share $\bar{s}$ to obtain

$$\widehat{s_{ht}} = \frac{\eta(1-\bar{s})}{\eta(1-\bar{s})+\bar{s}} \left(\widehat{\alpha_{ht}} + (1 - \frac{\rho}{\eta}) \widehat{p_{it}} - (1 - \frac{1}{\eta}) \widehat{x_{ht}} \right) \tag{1.20}$$

where $\widehat{y}$ denotes the log-deviation of a variable y from its mean. Defining $\beta_{ht} \equiv \frac{\eta(1-\bar{s})}{\eta(1-\bar{s})+\bar{s}} \widehat{\alpha_{ht}}$, $\theta \equiv \frac{\eta(1-\bar{s})}{\eta(1-\bar{s})+\bar{s}}(1 - \frac{\rho}{\eta})$ and $\zeta \equiv -\frac{\eta(1-\bar{s})}{\eta(1-\bar{s})+\bar{s}}(1 - \frac{1}{\eta})$, equation (1.20) simplifies to

$$\widehat{s_{ht}} = \beta_{ht} + \theta \widehat{p_{it}} + \zeta \widehat{x_{ht}}. \tag{1.21}$$

Under the null of homothetic preferences, $\theta = \zeta = 0$. I bring equation (1.21) to the data by modeling the demand shifter β_{ht} as a function of year fixed effects, observables, and an additive error. Formally, I get

$$\widehat{s_{ht}} = \beta_t + \theta \widehat{p_{it}} + \zeta \widehat{x_{ht}} + \delta X_{ht} + \epsilon_{ht} \tag{1.22}$$

where X_{ht} is a vector of demographic characteristics which include household size, the number of earners in the household as well as the gender and age of the household head. I observe total expenditure x_{ht}, the housing expenditure share s_{ht} (housing expenditure divided by total expenditure), and prices p_{it}. The error term ϵ_{ht} represents measurement error in expenditure plus random shocks to housing demand which both are assumed to be uncorrelated with expenditure and prices conditional on the controls. In my preferred specification, I estimate the nonlinear equation (1.19) directly by GMM.

Since expenditure data is only available from 2010 to 2014, I restrict my sample to these years. I drop households in the top and bottom 1% of the income and expenditure distribution each year to guard against serious misreporting errors. I further restrict the sample to renters. Since homeownership rates are increasing with income and homeowners spend on average less on housing than renters, I expect my estimates to be a lower bound of non-homotheticity. Finlay and Williams (forthcoming) use data on housing expenditures of homeowners and find similar results to those for renters.

Table 1.2: Preference Estimates

Dependent variable: Log housing expenditure share

	(1) OLS	(2) OLS IV	(3) OLS	(4) OLS IV	(5) GMM	(6) GMM IV
Log expenditure	-0.477***	-0.212***	-0.529***	-0.270***		
	(0.013)	(0.021)	(0.012)	(0.021)		
Log price			0.311***	0.233***		
			(0.017)	(0.017)		
eta			2.576***	1.520***	1.746***	1.807***
			(0.079)	(0.057)	(0.025)	(0.028)
rho			1.649***	1.072***	0.643***	0.598***
			(0.066)	(0.044)	(0.034)	(0.036)
Demogr. controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
R2	.275	.199	.331	.205		
adj. R2	.274	.196	.298	.201		
First stage F-stat.		3582		3242		
N	8232	8232	8232	8232	8232	8232
No. of clusters	4659	4318	4659	4318	4659	4318

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors in parentheses, clustered at the household level. Renters only. Instrument is log family income. Demographic controls include household size, number of earners as well as gender and age of the household head.

The estimation results are shown in Table 1.2. To deal with measurement error in expenditure, I follow Finlay and Williams (forthcoming) and use income as an instrument for expenditure. I find an expenditure elasticity of $\zeta = -0.27$ which is in line with estimates found in the literature that range from -0.88 to -0.01 (see the literature review in Finlay and Williams, forthcoming). Controlling for house prices on the district level increases the absolute size of the expenditure elasticity. Since higher income households sort into expensive regions, the estimated elasticity will be biased toward zero when not controlling for house prices. Offsetting price and income effects are in line with the findings of Albouy et al. (2016) and Finlay and Williams (forthcoming).

Finally, column (6) shows my preferred specification where I estimate the nonlinear equation (1.19) directly by GMM and instrument for expenditure. I estimate $\rho = 0.60$ and $\eta = 1.81$. Finlay and Williams (forthcoming) find estimates of the price elasticity $\theta = 0.39$ and the expenditure elasticity $\zeta = -0.25$. Assuming a mean housing expenditure share of $\bar{s} = 0.29$ as observed in the data, these estimates imply $\rho = 0.78$ and $\eta = 1.44$.[8] I follow Finlay and Williams (forthcoming) and compare the preferences estimated in Table 1.2 to two benchmarks from the literature: Cobb-Douglas preferences and a unit housing requirement. GES preferences as estimated above nest both of these special cases. The null hypothesis of Cobb-Douglas preferences, corresponding to $\rho \to 1$ and $\eta = 1$, can be rejected at the 1% level. A unit housing requirement corresponds to $\eta \to \infty$. Column (6) allows me to reject the null hypothesis that $\eta = 1.87$ or any number above at the 1% level.

Housing congestion γ_H

To calibrate the elasticity of housing supply to population, I combine equation (1.9) and (1.10) and solve for p_{it}

$$p_{it} = \frac{1-\gamma}{\gamma}\frac{\rho-\eta}{\rho-1}\left(\frac{\sum_k L_{ikt} c_{ikt}^{\frac{1}{\eta}}}{H_{it}}\right)^{\frac{\eta}{\rho}}. \tag{1.23}$$

The elasticity of house prices with respect to population is

$$\mathcal{E}_k \equiv \frac{\partial p_{it}}{\partial L_{ikt}}\frac{L_{ikt}}{p_{it}} = \frac{\eta}{\rho}\left(\frac{L_{ikt} c_{ikt}^{\frac{1}{\eta}}}{\sum_k L_{ikt} c_{ikt}^{\frac{1}{\eta}}} - \gamma_H \frac{L_{ikt}}{L_{it}}\right). \tag{1.24}$$

Summing over k yields

$$\sum_k \mathcal{E}_k = \frac{\eta}{\rho}(1-\gamma_H). \tag{1.25}$$

[8] In Appendix 1.A.2, I show that my results are close to Finlay and Williams (forthcoming) when estimating preference parameters from non-homothetic constant elasticity of substitution preferences, the utility function assumed by Finlay and Williams (forthcoming), using GMM.

Assuming equal elasticities for all worker types

$$\mathcal{E} = \frac{1}{K}\frac{\eta}{\rho}(1-\gamma_H). \tag{1.26}$$

where K denotes the number of worker groups. I take the parameter $\mathcal{E} = 0.208$ from Combes et al. (2019) which implies $\gamma_H = 1 - K\frac{\rho}{\eta}\mathcal{E} = 0.861$.

Scale parameter γ

The scale parameter γ is not identified separately from the scale of prices and consumption, so I normalize it to match the aggregate housing share. Plugging $x_{ikt} = \frac{c_{ikt}}{1-s_{ikt}}$ into equation (1.18), I get

$$\frac{s_{ikt}}{1-s_{ikt}} = \left(\frac{1-\gamma}{\gamma}\frac{\rho-\eta}{\rho-1}\right)^{\frac{\rho}{\eta}} \frac{p_{it}^{1-\frac{\rho}{\eta}}}{c_{ikt}^{1-\frac{1}{\eta}}} \tag{1.27}$$

which I numerically solve for s_{ikt} and γ using the additional constraint that the mean housing expenditure share matches the observed data ($\frac{1}{L_t}\sum_i \sum_k L_{ikt}s_{ikt} \approx 0.29$).

Table 1.3: Calibrated Parameters

Parameter	Value	Source
Preferences		
ρ	0.60	Estimated
η	1.81	Estimated
ψ	0.5	Gaubert et al. (forthcoming)
Congestion forces		
γ_H	0.86	Combes et al. (2019), own calculation

1.4.3 Structural fundamentals

I obtain the location-specific productivity, housing supply and amenity shifters A_{ikt}, T_{it} and E_{ikt} by inverting the model so that it exactly matches the observed data on p_{it}, w_{ikt} and L_{ikt} for all regions i and skill types k in

2007 and 2017. Abstracting from income taxes, social security contributions and transfers, I set $t_{ikt} = 0$.[9] From equation (1.6), I calculate productivity fundamentals

$$A_{ikt} = w_{ikt}. \tag{1.28}$$

Plugging housing supply (equation (1.7)) and housing demand (equation (1.10)) in the housing market clearing condition (equation (1.9)), I get an expression for the housing supply shifter that depends solely on variables that I observe in the data

$$T_{it} = L_{it}^{-\gamma_H}\left(\frac{1}{p_{it}}\frac{\rho-\eta}{\rho-1}\frac{1-\gamma}{\gamma}\right)^{\frac{\rho}{\eta}}\sum_k L_{ikt}(w_{ikt}+t_{ikt})^{\frac{1}{\eta}}. \tag{1.29}$$

Finally, I combine the mobility constraint (equation (1.4)) with the budget constraint (equation (1.2)) to get an equation that I can numerically solve for amenities E_{ikt}

$$L_{ikt} = \frac{\left((\gamma(w_{ikt}+t_{ikt})^{1-\frac{1}{\rho}}+(1-\gamma)h_{ikt}^{1-\frac{\eta}{\rho}})^{\frac{\rho}{\rho-1}}E_{ikt}\right)^{\frac{1}{\psi}}}{\sum_i\left((\gamma(w_{ikt}+t_{ikt})^{1-\frac{1}{\rho}}+(1-\gamma)h_{ikt}^{1-\frac{\eta}{\rho}})^{\frac{\rho}{\rho-1}}E_{ikt}\right)^{\frac{1}{\psi}}}L_{kt}$$

with housing demand from equation (1.10):

$$h_{ikt} = \left(\frac{1}{p_{it}}\frac{1-\gamma}{\gamma}\frac{\rho-\eta}{\rho-1}\right)^{\frac{\rho}{\eta}}(w_{ikt}+t_{ikt})^{\frac{1}{\eta}}. \tag{1.30}$$

1.5 Results

1.5.1 Decomposing changes in house prices and sorting

I use the calibrated model to quantify the importance of accounting for non-homothetic preferences when analyzing geographic worker sorting. To

[9] There are no location-specific income taxes in Germany. Note that linear taxes do not change the results in the case of Cobb-Douglas preferences. I abstract from non-linearities due to GES preferences and from non-linearities in income taxes, social security contributions and transfers.

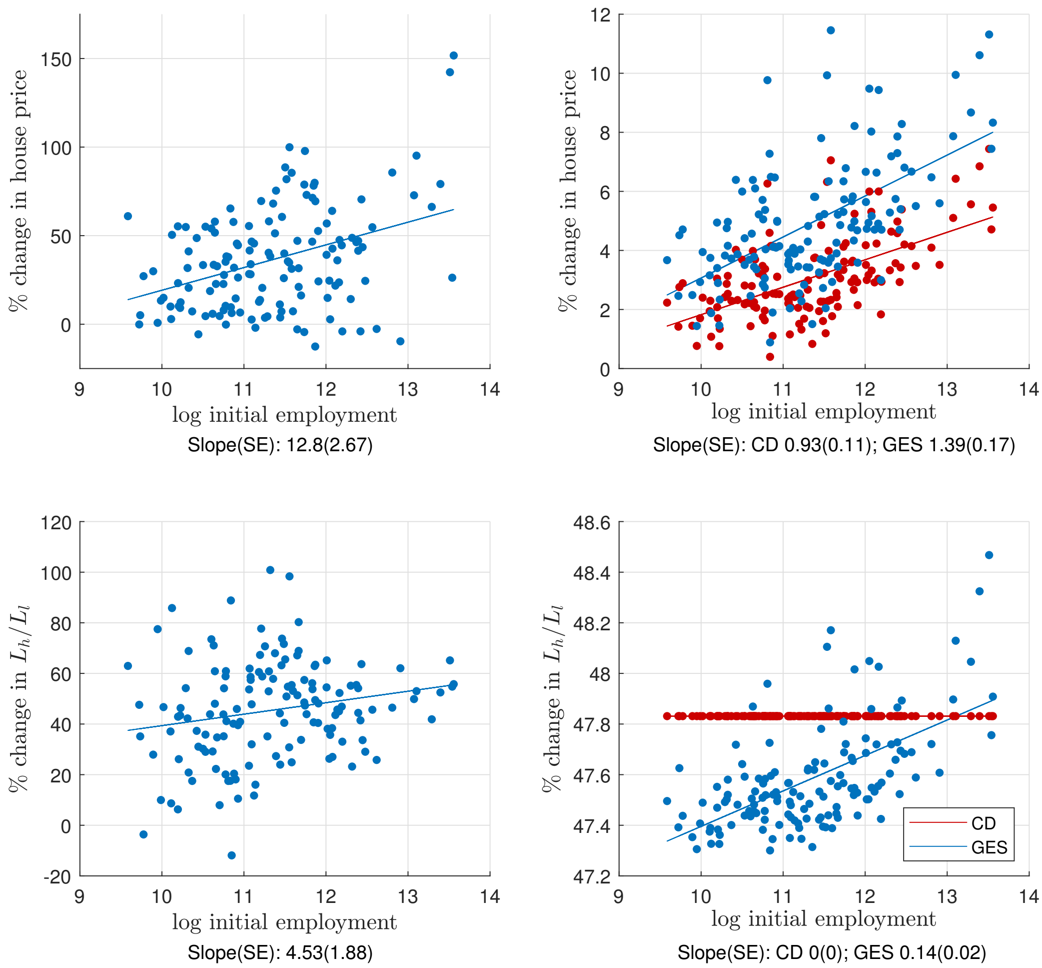
do so, I estimate the effect of the rise in housing congestion resulting from the national growth in the relative supply of high skilled workers. The shock amounts to an increase in the share of high skilled workers from 16% in 2007 to 22% in 2017. I plot a decomposition of the increase in the regional dispersion of house prices and the increase in skill sorting from 2007 to 2017. I compare the decomposition results obtained from a model with non-homothetic preferences with those from a model with constant housing expenditure shares. When assuming Cobb-Douglas preferences, I calibrate the scale paraemter γ to match the mean housing expenditure share observed in the data. However, by calibrating $\rho \to 1$ and $\eta = 1$, I do not match any other moments obtained from the GSOEP consumption microdata.

The left panels of Figure 1.3 plot changes as observed in the data, while the right panels isolate changes resulting from the national increase in the relative supply of high skilled workers. I plot data in a counterfactual scenario in which the national skill share increases as observed in the data while fundamentals remain at their 2007 level. The upper left panel of Figure 1.3 illustrates that the increase in housing congestion is more pronounced in large regions. I find that the national change in the relative supply of high skilled workers can explain 11% of the regional dispersion in house price increases (see the upper right panel of Figure 1.3). With homothetic Cobb-Douglas preferences, a change in the national skill share can explain only 7% of the regional dispersion in house price increases.

Why do house price differences increase more with GES preferences? With non-homothetic preferences, geographic worker sorting intensifies since low skilled workers are hit harder by increases in housing costs that are more pronounced in skill-intensive regions. The increase in skill sorting, in turn, amplifies differences in house price increases. The slope parameters in the lower panels quantify the change in skill sorting. The parameter in the data is 4.53, while in the counterfactual scenario, I find a slope parameter of 0.14. These values indicate that the national change in the relative supply of high skilled workers can explain 3% of the observed change in skill sorting. With homothetic preferences, there is no change in worker sorting.

Next, I calculate welfare changes implied by the national increase in the relative supply of high skilled workers. I measure the change in pre-shock tradable good consumption that would make workers as bad off as after the

Figure 1.3: Decomposition of changes in sorting and house prices



Note: Unit of observation is 141 labor market areas as defined by Kosfeld and Werner (2012). The left panels show changes in house prices and sorting as observed in the data from 2007 to 2017. The right panels show changes in house prices and sorting in a counterfactual scenario in which the national skill share increases as observed in the data while fundamentals remain at their 2007 level.

shock. I equalize expected utility as defined in equation (1.11) before and after the shock

$$u^{exp}\left((1+\Delta_k^{sh})c_{ik2007}, h_{ik2007}, E_{ik2007}\right) = u^{exp}\left(c_{ik}^{sh}, h_{ik}^{sh}, E_{ik}^{sh}\right) \tag{1.31}$$

where $c_{ik2007}, h_{ik2007}, E_{ik2007}$ are consumption and amenities in the observed allocation, and $c_{ik}^{sh}, h_{ik}^{sh}, E_{ik}^{sh}$ are values in the counterfactual scenario in which the national share of high skilled workers changes as in the data, while fundamentals remain as in 2007. Solving numerically for Δ_k^{sh}, I find that the increase in the national share of high skilled workers has decreased expected utility of high skilled workers by 0.8% and expected utility of low skilled workers by 0.9%. Since low skilled workers spend a larger share of their income on housing, they were hit harder by increases in housing congestion.

1.5.2 The size of inefficiencies

After having explored the importance of allowing for non-homothetic preferences when analyzing sorting in a spatial equilibrium model, I next estimate the optimal degree of sorting. To do so, I solve the problem of a social planner who uses transfers between locations and worker types which change the spatial distribution of economic activity. By changing the location incentives of workers, they affect spatial sorting and the spatial concentration of population. These reallocations in turn impact house prices, which feed back to location choices. In the following, I describe the spatial equilibrium resulting from this process.

I start by calibrating the welfare weights ω_{kt} such that both worker types experience the same welfare gain as compared to the observed allocation. I measure welfare gains as the change in tradable good consumption that would make workers in the observed allocation as well off as moving to the optimal allocation. Similarly to the measurement in equation (1.31), I obtain the welfare change Δ^*_{kt} from numerically solving

$$u^{exp}\left((1+\Delta^*_{kt})c_{ikt}, h_{ikt}, E_{ikt}\right) = u^{exp}\left(c^*_{ikt}, h^*_{ikt}, E^*_{ikt}\right) \tag{1.32}$$

where $c_{ikt}, h_{ikt}, E_{ikt}$ are consumption and amenities in the observed allocation, while $c^*_{ikt}, h^*_{ikt}, E^*_{ikt}$ are values in the optimal allocation.[10]

Figure 1.4 illustrates the transfer scheme that implements the optimal allocation. Both in 2007 and 2017, it is optimal to set incentives for high and low skilled workers to move toward less populated areas. As formally

[10]Note that calibrating welfare weights such that welfare gains are equal for both worker types implies welfare weights to be differentially calibrated for 2007 and 2017. However, when estimating the social planner solution, I find negligible changes in welfare weights: Calibrating the welfare weights to sum up to 1 ($\sum_k \omega_{kt} = 1$), I find the social planner to choose a weight for high skilled workers of 0.627 in 2007 and of 0.639 in 2017. The results are robust to calibrating the welfare weights in 2017 to the weights found for the calibration in 2007.

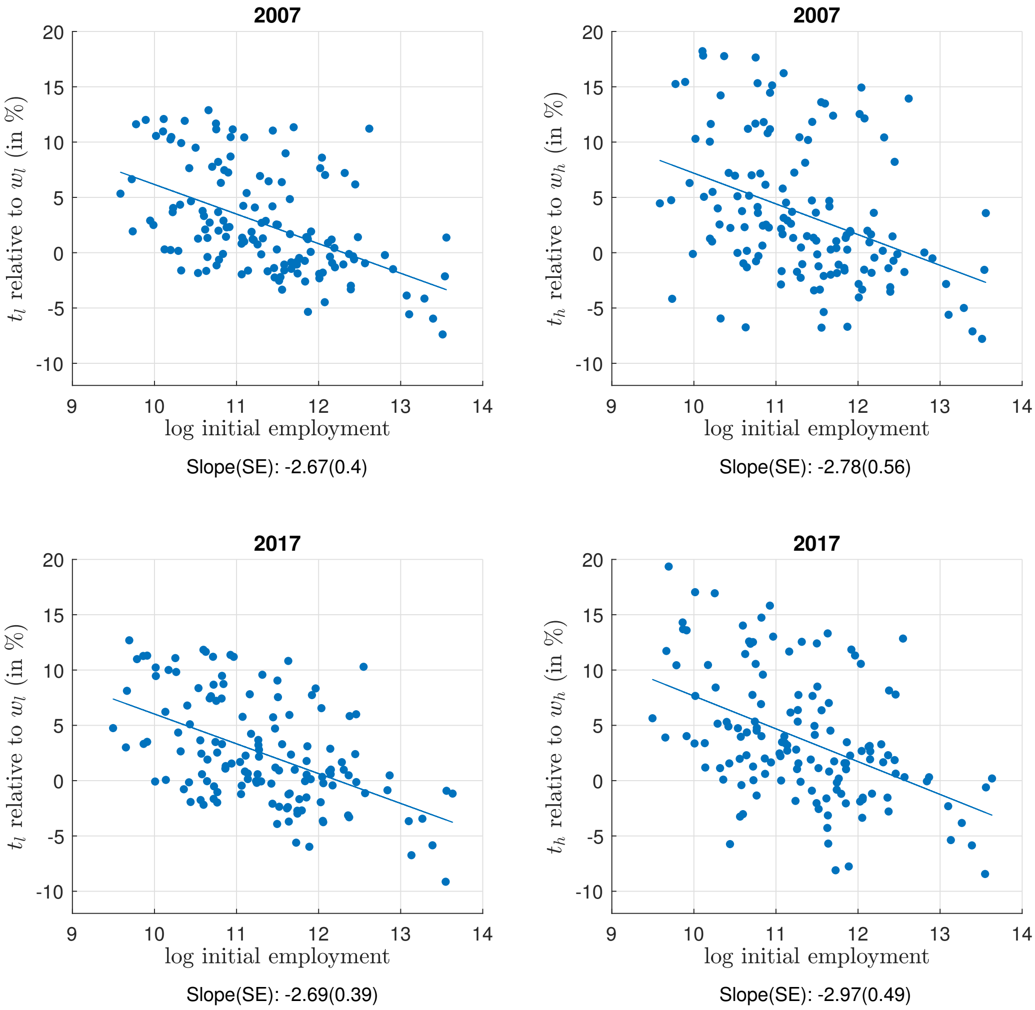
shown in Section 1.3.2, the social planner takes into account redistribution and efficiency considerations when choosing a regional skill-specific transfer scheme. In terms of efficiency, it is optimal to set larger transfers in rural areas because I include only negative externalities in the form of housing congestion. In terms of redistribution, optimal transfers are larger in rural areas since wages are on average lower than in urban areas which implies larger marginal utilities of tradable good consumption. It is therefore intuitive that the spatial concentration of population is smaller in the optimal allocation as compared to the observed allocation.

As illustrated in the upper panels of Figure 1.5, it is further optimal to decrease skill sorting by moving a larger share of high skilled workers toward less populated regions. Since high skilled workers, by consuming more housing than low skilled workers, generate larger congestion forces, it is optimal to reallocate them to a larger extent toward regions with less congested housing markets. Furthermore, since the urban wage premium is larger for high skilled workers, spatial differences in marginal utilities of tradable good consumption are larger for high skilled than for low skilled workers.[11] The smaller degree of agglomeration and skill sorting in the optimal allocation imply that house prices are less dispersed as reflected in a larger increase in house prices in rural as compared to urban areas.

How should transfers adjust to changes from 2007 to 2017? Figure 1.4 illustrates that in 2017, optimal policies imply a greater degree of redistribution between regions compared to 2007. A larger dispersion in transfers, in turn, implies larger incentives to move across space. The upper panels of Figure 1.5 show that it is optimal to decrease sorting by 70% more than in 2007: The slope parameter decreases from -0.41 in 2007 to -0.7 in 2017. In Figure 1.A.3, it can be seen that the urban wage premium has decreased more for high school graduates, which implies that the stronger decrease in sorting in 2017 is driven by efficiency considerations rather than differences in marginal utilities of consumption. Since sorting has increased from 2007 to 2017, congestion externalities generated by high skilled workers have increased to a larger extent than those generated by low skilled workers. It is therefore optimal from a social planner perspective to decrease sorting more than in 2007. As a consequence, moving from the observed to the optimal

[11]The urban wage premium is plotted in Figure 1.A.3.

Figure 1.4: Optimal transfers

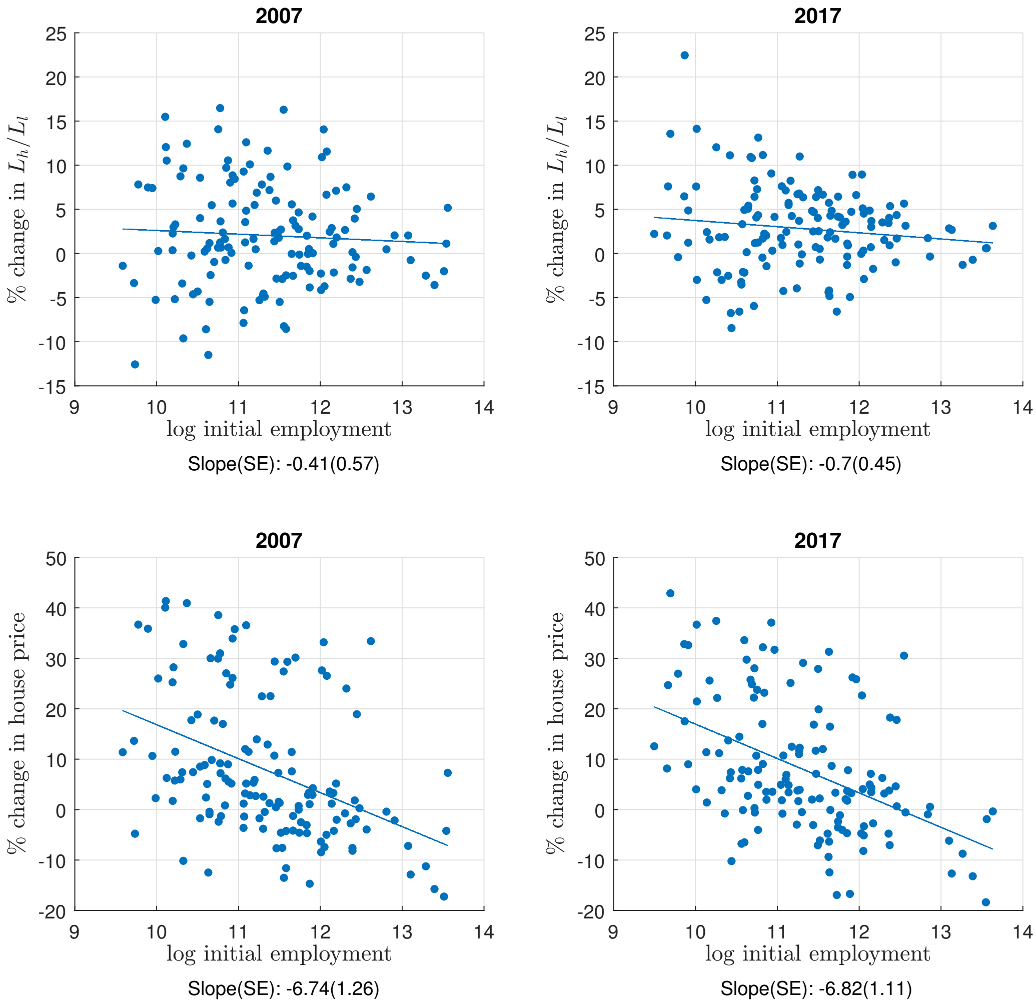


Note: Unit of observation is 141 labor market areas as defined by Kosfeld and Werner (2012). The plots show optimal transfers for low and high skilled workers relative to their wage. The planner's weights are chosen such that both types of workers experience the same welfare gains.

allocation implies a larger decrease in house price differences between rural and urban areas than in 2007, as shown in the lower panels of Figure 1.5.

Next, I allow for differential welfare gains for workers with and without a university degree moving from the observed to the optimal allocation. Figure 1.6 plots the utility frontier obtained from solving for the optimal allocation on a grid of welfare weights ω_{kt}. Welfare gains are measured as given in Equation (1.32). I choose the grid of welfare weights such that welfare gains for both worker types are positive. I find that for any combination of welfare

Figure 1.5: Optimal sorting and house prices

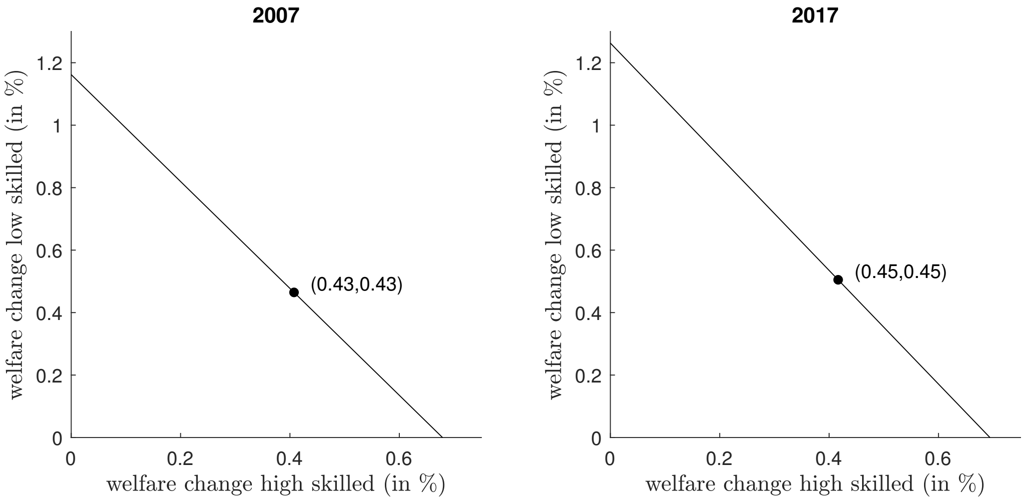


Note: Unit of observation is 141 labor market areas as defined by Kosfeld and Werner (2012). The plots show the change in skill sorting and house prices between the observed equilibrium and the optimal allocation. The planner's weights are chosen such that both types of workers experience the same welfare gains.

gains, the benefits from moving from the observed to the optimal allocation are larger in 2017 than in 2007. When both worker types benefit equally, welfare gains amount to 0.43% of tradable good consumption in 2007 and 0.45% in 2017. Since sorting and the spatial dispersion in house prices have increased from 2007 to 2017, it is optimal to redistribute more in 2017, which implies larger welfare gains.

Both in 2007 and 2017, the maximum possible welfare gain of low skilled workers is substantially larger than that of high skilled workers. Focusing on

Figure 1.6: Utility frontier between high and low skilled workers



Note: The plots show the change in welfare between the observed equilibrium and the optimal allocation. Welfare changes are measured as the percentage change in tradable good consumption in the observed allocation that would make the worker as well off as moving to the optimal allocation.

welfare weights that imply positive welfare changes for both worker types, low skilled workers can gain more than 1.2% from moving from the observed to the optimal allocation in 2017, while welfare gains for high skilled workers do not exceed 0.7%. Since low skilled workers spend a larger share of their income on housing, the benefit from decreasing housing congestion is larger for low skilled than for high skilled workers.

1.6 Conclusion

With non-homothetic preferences, an increase in the national relative supply of college graduates intensifies spatial sorting. The reason is that low skilled workers are hit harder by increases in housing costs that are more pronounced in skill-intensive regions. The increase in sorting, in turn, amplifies house price increases in large cities as compared to rural areas. The growth in the relative supply of high skilled workers between 2007 and 2017 in Germany has caused skilled households to increasingly move toward high-cost regions and unskilled households to move toward low-cost regions. My model attributes about 11% of the regional differences in house price increases and 3% of the increase in spatial sorting to the growth in the national share of high skilled workers. Intensified skill sorting implied small negative welfare effects and slight increases in well-being inequality between workers of different skills. From a social planner perspective, it would be optimal to respond to the observed trends by setting incentives for both worker types to move toward less expensive regions, but to set larger incentives for high skilled workers.

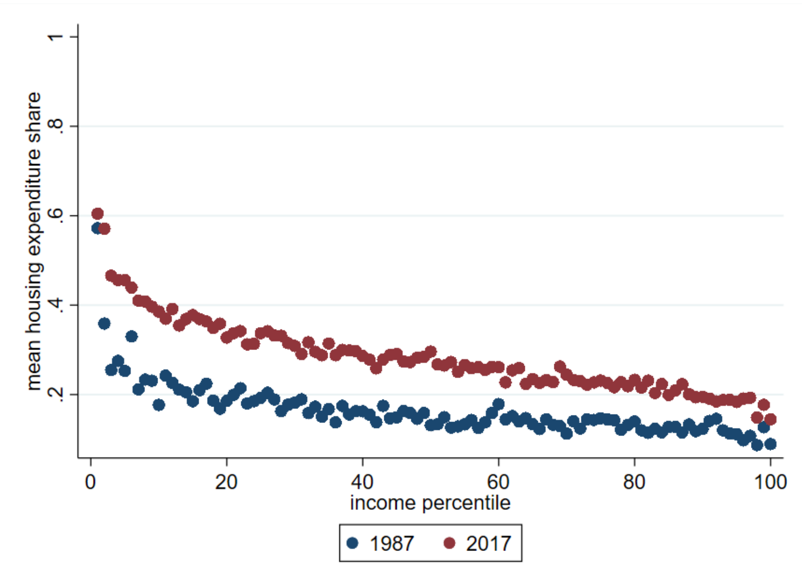
To isolate the effect of non-homothetic housing demand on spatial sorting, I have presented a simple and tractable model that abstracts from externalities in amenities and production. It would be interesting to incorporate such spillovers into the model to examine the feedback from the spatial distribution of skills to wages and amenities. This extension might provide valuable insights into the optimal design of place-based policies, making it a promising direction for future research.

1.A Quantification appendix

1.A.1 Stylized facts

To analyze how hard increases in housing costs have hit households across the income distribution, I plot housing expenditure shares in 1987 compared to housing expenditure shares in 2017. Figure 1.A.1 provides suggestive evidence that the decrease in housing affordability is mainly a problem of low income households: The housing expenditure share has increased significantly more for low income than for high income households.

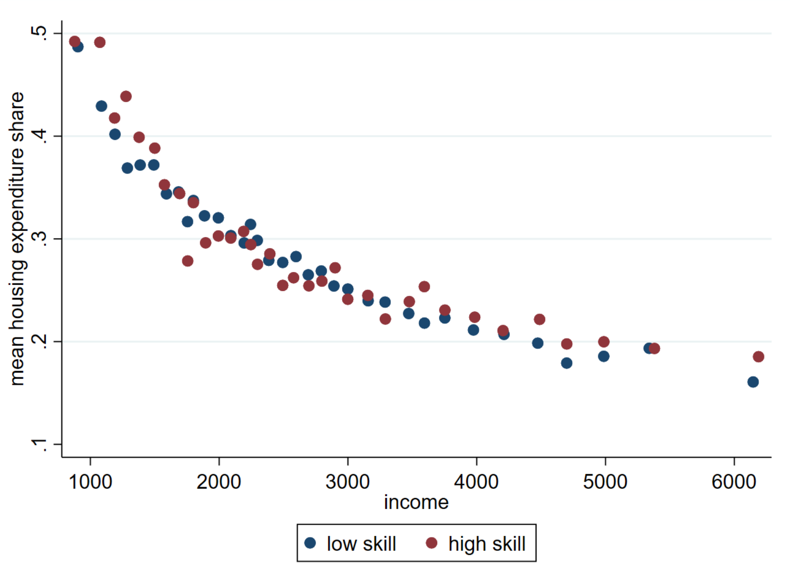
Figure 1.A.1: Changes in housing expenditure shares



Note: West Germany only. Housing expenditure share is defined as housing expenditure (including heating and electricity) divided by total net income. Number of observations: 2725 in 1987, 5188 in 2017

Next, I investigate whether differences in housing expenditure shares are driven by education levels rather than income. Figure 1.A.2 plots housing expenditure shares for 50 evenly sized bins defined by total income separately for households with a household head not holding a university degree and households with a household head holding a university degree. It can be seen that for given income levels, the two types of households do not spend different shares of their expenditure on housing.

Figure 1.A.2: Housing expenditure shares by skill



Note: The plot shows mean housing expenditure shares for 50 evenly sized bins defined by total income. Housing expenditure share is defined as housing expenditure (including heating and electricity) divided by total net income. The plot is based on household data from 2017. Skill refers to the skill of the household head. Number of observations: 3259 low skill, 1322 high skill

1.A.2 Calibration

I compare my non-homotheticity estimates to those assuming non-homothetic constant elasticity of substitution (NHCES) preferences as applied in Finlay and Williams (forthcoming)

$$U_{ikt}^{\frac{\sigma-1}{\sigma}} = \Omega^{\frac{1}{\sigma}} h_{ikt}^{\frac{\sigma-1}{\sigma}} U_{ikt}^{\frac{\epsilon}{\sigma}} + c_{ikt}^{\frac{\sigma-1}{\sigma}} \tag{1.33}$$

where $0 < \sigma < 1$, $\epsilon \geq \sigma - 1$, and $\Omega > 0$ are parameters. Cobb-Douglas preferences are obtained by taking $\epsilon = 0$ and $\sigma \to 1$. The opposite case, a unit housing requirement, is obtained by taking $\epsilon = -1$ and $\sigma \to 0$. Instead of equation (1.18), I get

$$s_{ikt} = \Omega p_{it}^{1-\sigma} x_{ikt}^{\epsilon} (1 - s_{ikt})^{1+\frac{\epsilon}{1+\sigma}}. \tag{1.34}$$

I estimate equation (1.34) by GMM. The results as given in Table 1.A.1 are similar to those in Finlay and Williams (forthcoming) who find $\epsilon = -0.306$ and $\sigma = 0.522$.

Table 1.A.1: Preference Estimates for NHCES Preferences

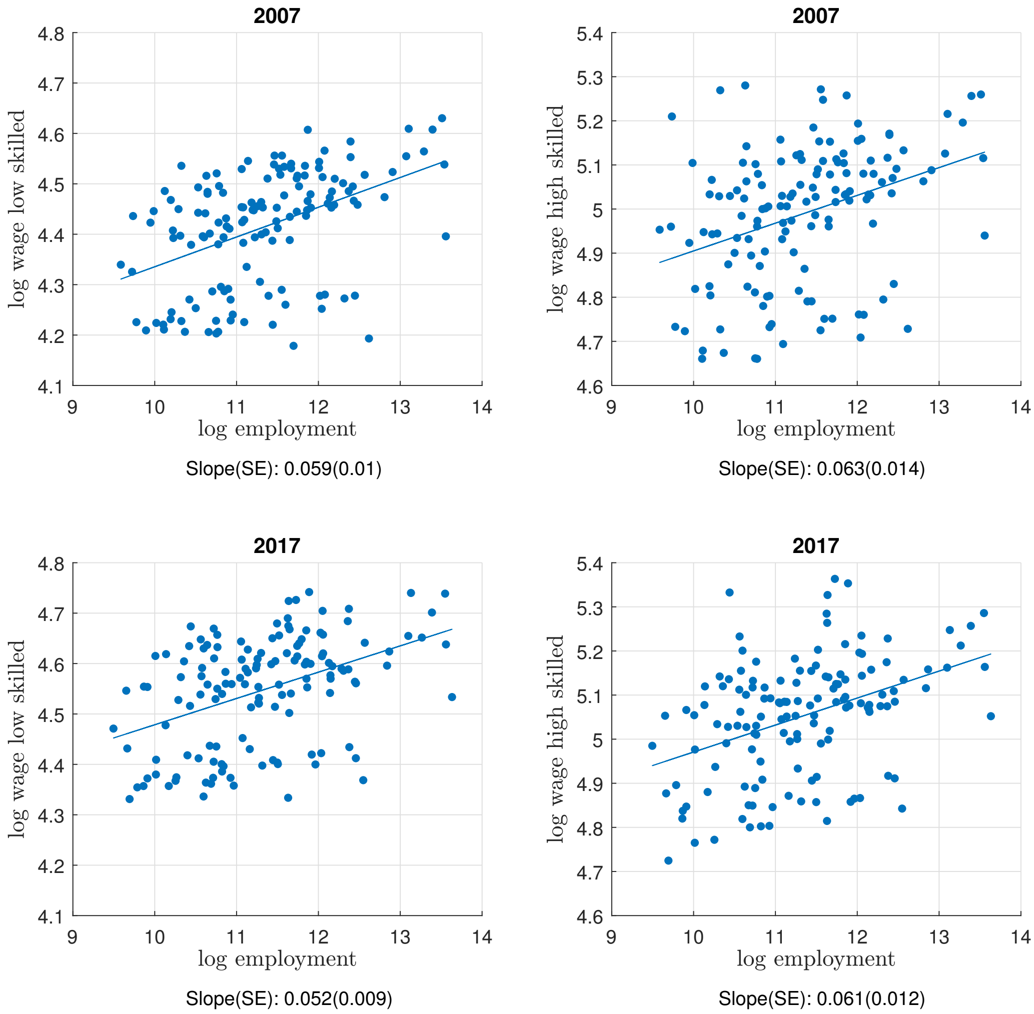
	(1) GMM	(2) GMM IV
ϵ	-0.299***	-0.301***
	(0.003)	(0.003)
σ	0.882***	0.886***
	(0.002)	(0.002)
Demographic controls	✓	✓
Year FE	✓	✓
N	8232	8232
No. of clusters	4659	4318

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors in parentheses, clustered at the household level. Renters only. Instrument is log family income. Demographic controls include household size, number of earners as well as gender and age of the household head.

1.A.3 The urban wage premium

Figure 1.A.3: The urban wage premium by skill



Note: Unit of observation is 141 labor market areas as defined by Kosfeld and Werner (2012). The plot shows average gross daily wages. Low skilled refers to workers with a high school degree, high skilled are workers with a college degree.

1.B Model appendix - Constrained efficient allocation

1.B.1 Additional derivations

The problem of the social planner maximizing ex-ante utility with the constraint that she does not know the realizations of the idiosyncratic shocks can be written as

$$\begin{aligned}
\max_{c_{ikt},h_{ikt},L_{ikt}} \mathcal{L} &= \sum_k \omega_{kt}\psi \log\left(\sum_i e^{\frac{\frac{\rho}{\rho-1}\log\left(\gamma c_{ikt}^{1-\frac{1}{\rho}}+(1-\gamma)h_{ikt}^{1-\frac{\eta}{\rho}}\right)+\log E_{ikt}}{\psi}}\right) \\
&- \sum_k\sum_i \lambda_{ikt}\left(\frac{\left((\gamma c_{ikt}^{1-\frac{1}{\rho}}+(1-\gamma)h_{ikt}^{1-\frac{\eta}{\rho}})^{\frac{\rho}{\rho-1}}E_{ikt}\right)^{\frac{1}{\psi}}}{\sum_i\left((\gamma c_{ikt}^{1-\frac{1}{\rho}}+(1-\gamma)h_{ikt}^{1-\frac{\eta}{\rho}})^{\frac{\rho}{\rho-1}}E_{ikt}\right)^{\frac{1}{\psi}}}L_{kt}-L_{ikt}\right) \\
&- \mu_t^Y\sum_i\sum_k(L_{ikt}c_{ikt}-L_{ikt}A_{ikt}) \\
&- \sum_i \mu_{it}^h\left(\sum_k L_{ikt}h_{ikt}-T_{it}L_{it}^{\gamma_H}\right)
\end{aligned}$$

where I omit notation for the non-negativity constraints and solve for interior solutions. Fajgelbaum and Gaubert (2020) show that the social planner problem is concave when congestion forces are at least as large as agglomeration forces. The facts that my model features congestion forces only and that the generalization of non-homothetic preferences does not act as an agglomeration force ensure that there is a unique solution to the maximization problem. The first-order conditions are given by

$$[h_{ikt}]\quad \eta_{it}^h L_{ikt}h_{ikt} = \frac{\frac{\rho-\eta}{\rho-1}(1-\gamma)h_{ikt}^{1-\frac{\eta}{\rho}}}{\gamma c_{ikt}^{1-\frac{1}{\rho}}+(1-\gamma)h_{ikt}^{1-\frac{\eta}{\rho}}}\left[\omega_{kt}L_{ikt}-\frac{\lambda_{ikt}L_{ikt}}{\psi}+\sum_j\lambda_{jkt}\frac{L_{jkt}L_{ikt}}{\psi}\right]$$

$$[c_{ikt}] \quad \eta_t^Y L_{ikt} c_{ikt} \quad = \quad \frac{\gamma c_{ikt}^{1-\frac{1}{\rho}}}{\gamma c_{ikt}^{1-\frac{1}{\rho}} + (1-\gamma) h_{ikt}^{1-\frac{\eta}{\rho}}} \Big[\omega_{kt} L_{ikt} - \frac{\lambda_{ikt} L_{ikt}}{\psi} + \sum_j \lambda_{jkt} \frac{L_{jkt} L_{ikt}}{\psi} \Big]$$

$$[L_{ikt}] \quad \lambda_{ikt} \quad = \quad \mu_t^Y (c_{ikt} - A_{ikt}) + \mu_{it}^h \Big(h_{ikt} - \frac{\partial H_{it}}{\partial L_{ikt}} \Big)$$

I have Tx(4xIxK+I+1) equations in $L_{ikt}, c_{ikt}, h_{ikt}, \lambda_{ikt}, \mu_{it}^h$ and μ_t^Y:

- Dividing $[h_{ikt}]$ through $[c_{ikt}]$ gives housing demand

$$h_{ikt} = \Big(\frac{\mu_t^Y}{\mu_{it}^h} \frac{\rho - \eta}{\rho - 1} \frac{1-\gamma}{\gamma} \Big)^{\frac{\rho}{\eta}} c_{ikt}^{\frac{1}{\eta}} \tag{1.35}$$

- Optimal consumption $[c_{ikt}]$

$$\frac{\mu_t^Y}{\gamma} c_{ikt} \Bigg(\gamma + (1-\gamma) \frac{h_{ikt}^{1-\frac{\eta}{\rho}}}{c_{ikt}^{1-\frac{1}{\rho}}} \Bigg) \quad = \quad \omega_{kt} - \frac{\lambda_{ikt}}{\psi} + \sum_j \lambda_{jkt} \frac{L_{jkt}}{\psi} \tag{1.36}$$

- Optimal labor allocation $[L_{ikt}]$

$$\lambda_{ikt} \quad = \quad \mu_t^Y (c_{ikt} - A_{ikt}) + \mu_{it}^h \Big(h_{ikt} - \frac{\partial H_{it}}{\partial L_{ikt}} \Big) \tag{1.37}$$

- Mobility constraint

$$L_{ikt} \quad = \quad \frac{\Big((\gamma c_{ikt}^{1-\frac{1}{\rho}} + (1-\gamma) h_{ikt}^{1-\frac{\eta}{\rho}})^{\frac{\rho}{\rho-1}} E_{ikt} \Big)^{\frac{1}{\psi}}}{\sum_i \Big((\gamma c_{ikt}^{1-\frac{1}{\rho}} + (1-\gamma) h_{ikt}^{1-\frac{\eta}{\rho}})^{\frac{\rho}{\rho-1}} E_{ikt} \Big)^{\frac{1}{\psi}}} L_{kt} \tag{1.38}$$

- Housing market clearing

$$\sum_k L_{ikt} h_{ikt} - H_{it} = 0 \tag{1.39}$$

- Balanced government budget

$$\sum_i \sum_k (L_{ikt} c_{ikt} - L_{ikt} A_{ikt}) = 0 \tag{1.40}$$

Decentralized vs. planner allocation

From $[L_{ikt}]$, I get

$$\mu_t^Y c_{ikt} + \mu_{it}^h h_{ikt} = w_{ikt} + \Pi_{ikt} + t_{ikt}$$

where I define

$$w_{ikt} \equiv \mu_t^Y A_{ikt} \tag{1.41}$$
$$\Pi_{ikt} \equiv \mu_{it}^h h_{ikt} \tag{1.42}$$

and

$$t_{ikt} \equiv \lambda_{ikt} + \mu_{it}^h \left(\frac{\partial H_{it}}{\partial L_{ikt}} - \Pi_{ikt} \right). \tag{1.43}$$

Together with housing demand in equation (1.35), the mobility costraint in equation (1.38) and the budget constraints in equation (1.39) and (1.40), I have the equilibrium conditions of the decentralized allocation with $\mu_t^Y = 1$ and $\mu_{it}^h = p_{it}$.

1.B.2 Solving the system of non-linear equations

To solve the system of equations numerically, I can substitute in the Lagrange multipliers and housing consumption to express the system of equations in terms of L_{ikt} and c_{ikt}. Combining housing demand in equation (1.10) with housing market clearing in equation (1.9), I get an expression for housing consumption that only depends on parameters, fundamentals, L_{ikt} and c_{ikt}:

$$h_{ikt} = \frac{c_{ikt}^{\frac{1}{\eta}}}{\sum_k L_{ikt} c_{ikt}^{\frac{1}{\eta}}} T_{it} L_{it}^{\gamma_H}. \tag{1.44}$$

Summing $[c_{ikt}]$ over i and normalizing population of each type to 1 ($\sum_i L_{ikt} = 1$) yields

$$\omega_{kt} = \frac{\mu_t^Y}{\gamma} \sum_i \left(\gamma L_{ikt} c_{ikt} + (1-\gamma) L_{ikt} h_{ikt}^{1-\frac{\eta}{\rho}} c_{ikt}^{\frac{1}{\rho}} \right) \tag{1.45}$$

which, after summing over k, can be rearranged to

$$\mu_t^Y = \frac{\gamma}{\sum_i \sum_k \left(\gamma L_{ikt} c_{ikt} + (1-\gamma) L_{ikt} h_{ikt}^{1-\frac{\eta}{\rho}} c_{ikt}^{\frac{1}{\rho}}\right)}. \tag{1.46}$$

Summing housing demand over k and rearranging, I obtain

$$\mu_{it}^h = \mu_t^Y \frac{1-\gamma}{\gamma} \frac{\rho-\eta}{\rho-1} \left(\frac{\sum_k c_{ikt}^{\frac{1}{\eta}}}{\sum_k h_{ikt}}\right)^{\frac{\eta}{\rho}}. \tag{1.47}$$

The first-order condition with respect to $[L_{ikt}]$ gives an expression for λ_{ikt}:

$$-\lambda_{ikt} = \eta_t^Y (A_{ikt} - c_{ikt}) + \mu_{it}^h \left(\frac{\partial H_{it}}{\partial L_{ikt}} - h_{ikt}\right). \tag{1.48}$$

Thus, after substituting in housing h_{ikt} and the Lagrange multipliers μ_t^Y, μ_{it}^h and λ_{ikt}, I have a system of 2xTxIxK equations which I numerically solve for L_{ikt} and c_{ikt}:

$$\frac{\mu_t^Y}{\gamma} c_{ikt} \left(\gamma + (1-\gamma) \frac{h_{ikt}^{1-\frac{\eta}{\rho}}}{c_{ikt}^{1-\frac{1}{\rho}}}\right) = \omega_{kt} - \frac{\lambda_{ikt}}{\psi} + \sum_j \lambda_{jkt} \frac{L_{jkt}}{\psi} \tag{1.49}$$

$$L_{ikt} = \frac{\left((\gamma c_{ikt}^{1-\frac{1}{\rho}} + (1-\gamma) h_{ikt}^{1-\frac{\eta}{\rho}})^{\frac{\rho}{\rho-1}} E_{ikt}\right)^{\frac{1}{\psi}}}{\sum_i \left((\gamma c_{ikt}^{1-\frac{1}{\rho}} + (1-\gamma) h_{ikt}^{1-\frac{\eta}{\rho}})^{\frac{\rho}{\rho-1}} E_{ikt}\right)^{\frac{1}{\psi}}} L_{kt}. \tag{1.50}$$

CHAPTER 2

The Impact of Demographics on Labor Market Power: An Analysis using German Administrative Data

Chapter Abstract

This chapter studies the degree of labor market power that firms have over workers of different demographic groups. I measure labor market power by estimating the sensitivity of worker turnover to the wage paid. Using rich German employer-employee data, I identify age-specific labor supply elasticities by comparing older with younger workers of the same gender and within the same industry and region. I find a strong role of demographics in determining the degree of labor market power enjoyed by firms: The labor supply elasticity decreases from more than 2 for the age group 20 to 29 to 1 for workers aged 60 to 64.

2.1 Introduction

Recently, there has been a growing number of studies on the prevalence and causes of labor market power. This new literature makes clear that there are various reasons for labor market power including not only concentration, but also search frictions, mobility costs, and match-specific amenities, all of which restrict workers' responsiveness to wages (see Card (2022) for an overview). By analyzing the elasticity of the labor supply curve perceived by firms, empirical studies try to determine if firms have a considerable degree of labor market power or if the perfect competition model is a good approximation. This literature has found that the labor supply elasticity is far from infinite, indicating that employers have substantial labor market power. Labor supply elasticities have also been found to be heterogeneous across workers. There is literature showing that the labor supply elasticity is lower for women (Barth and Dale-Olsen, 2009; Hirsch et al., 2010), for migrants (Hirsch and Jahn, 2015) and for workers in rural areas (Bamford, 2021; Hirsch et al., 2022). Understanding heterogeneities in labor supply elasticities is crucial because they imply that economic policies such as the minimum wage may have distributional impacts across many dimensions.

This chapter highlights an often overlooked dimension of heterogeneity in labor market power and empirically documents large differences in the sensitivity of worker turnover by age. Utilizing high-quality matched employer-employee data from Germany (Antoni et al., 2019), I follow Manning (2013) and estimate labor market power by measuring the sensitivity of worker turnover to the wage paid. This observational approach involves relating variation in the wage a worker is paid to the probability that there is an employment separation. Exploiting the rich structure of the panel data, I identify age-specific elasticities by comparing older with younger workers of the same gender and within the same industry and region. I find a strong role of demographics in determining the degree of labor market power enjoyed by firms: The labor supply elasticity decreases from more than 2 for the age group 20 to 29 to 1 for workers aged 60 to 64.

Although I do not analyze the drivers of differences in labor market power, several potential channels could rationalize my finding of a lower labor supply elasticity of older workers: A new match yields a lower surplus for both workers and firms when there is less time until retirement. Older workers might not only face higher search frictions but also larger costs of moving between employers due to psychological inertia. Finally, older workers might benefit more from non-pecuniary job aspects because of longer relations with colleagues.

My results further suggest that firms have more labor market power over low skilled workers with stronger differences for young workers. In the age group 20 to 29, I find a labor supply elasticity of 2.5 for workers with a university degree, while my estimate for workers without a university degree is less than 2. I further provide evidence that there are no differences in labor supply elasticities by gender for most age groups which is in contrast to previous literature finding lower labor supply elasticities of females (Barth and Dale-Olsen, 2009; Hirsch et al., 2010).

This chapter is related to several strands of literature. First, it is related to literature that estimates labor supply elasticities for different groups of workers. In addition to differences in labor supply elasticities by gender, it has been documented that migrants react less strongly to wages than natives (Hirsch and Jahn, 2015). Bamford (2021) and Hirsch et al. (2022) find evidence that labor market power is lower in larger labor markets. To the best of my knowledge, demographics have not been analyzed in the context of monopsonistic wage setting. However, it has been pointed out that tenure seems to matter. Manning (2013) argues that including tenure reduces the estimated wage elasticity as high-tenure workers are less likely to leave the firm and are more likely to have high wages. I find that while age and tenure are strongly correlated, the effect of age is significant even after controlling for tenure.

This work is further related to emerging literature on the effect of an aging population on market power. Bornstein (forthcoming) shows that population aging has increased product market power as older consumers are less likely to demand new varieties. The rise in consumer inertia leads large incumbents to raise their markups and profits while discouraging market entry. My work is complementary to but quite different from this paper since I argue that population aging increases labor market power rather than product market power. A number of recent papers suggest that the change in demographics has affected labor market power by decreasing the startup rate and increasing concentration (Liang et al., 2018; Hopenhayn et al., 2022; Karahan et al., forthcoming). Engbom (2019) argues that older workers are both less likely to switch employers and enter entrepreneurship because they have had more time to find a good job. While Engbom (2019) analyzes how firm and worker dynamics interact in equilibrium to amplify the effect of aging, I focus on worker dynamics to investigate how workers' responsiveness to wages evolves over the life cycle.

The remainder of the chapter is structured as follows. Section 2.2 describes the data and Section 2.3 outlines the model. Section 2.4 presents the regression results that reveal significant heterogeneity in labor supply elasticities by age and skill. It shows that the baseline results are robust to controlling for tenure and estimating skill-specific age coefficients. I furthermore document that labor supply elasticities do not differ by gender for most age groups. Section 2.5 concludes.

2.2 Data

I use the microdata on individual employment histories from the Sample of Integrated Labor Market Biographies (SIAB) provided by the Institute for Employment Research (IEB) covering the years 1975 to 2017 (Antoni et al., 2019). The SIAB is a 2% representative sample of administrative data on all workers who are subject to social security contributions in Germany, excluding self-employed and civil servants. I restrict the sample to full-time workers between 20 and 64 and use the consumer price index from Statistisches Bundesamt (2019) to calculate real wages. I only observe wages up to the social security contribution ceiling. To impute top-coded wages for the roughly 5% of observations above the social security contribution ceiling, I use the approach from Dauth and Eppelsheimer (2021). I obtain information on the workplace region and the sector from the Establishment History Panel (BHP) which is an establishment-level data set from social security records that can be merged with the SIAB. I drop the years before 1994 because data from East Germany is not available before 1991 and is incomplete up to 1993. Descriptive statistics are shown in Table 2.A.1.

2.3 Method

To estimate labor supply elasticities for different worker groups, I use the dynamic model of monopsonistic competition of Manning (2013) which is in turn based on the Burdett and Mortensen (1998) equilibrium search model. In the model, a stable equilibrium distribution of wages exists, both over workers and firms. Each worker receives job offers at an exogenous job offer rate. If the offered wage is higher than the wage paid in the current firm, the worker accepts and moves up the job ladder by switching firms. Consequently, firms have a constant flow of hirings and separations. I assume there are different worker groups k that are defined by the interaction of the age and the skill group. The distribution of job offers might differ across worker groups. $s(w_{fkt})$ is the separation rate of workers of type k at firm f in period t. It depends negatively on the wage, because at a high wage fewer firms will make a better wage offer in comparison to the current wage paid. The opposite is true for the number of recruits $R(w_{fkt})$. The total number of workers of type k in firm f at period t is denoted by L_{fkt}. It can be expressed as the sum of workers of group k who were already employed in firm f in the previous period L_{fkt-1} plus the number of recruits in period t denoted by $R(w_{fkt})$ minus the number of separations $s(w_{fkt})L_{fkt-1}$. The law of motion for labor supply to the firm can thus be expressed as

$$L_{fkt} = R(w_{fkt}) + [1 - s(w_{fkt})]L_{fkt-1}. \tag{2.1}$$

Considering the steady state, I get

$$L_{fk} = \frac{R(w_{fk})}{s(w_{fk})}. \tag{2.2}$$

This implies that the long-term elasticity of labor supply to the individual firm η_k can be expressed as

$$\eta_k = \eta_{Rk} - \eta_{sk} \tag{2.3}$$

where η_{Rk} is the wage elasticity of recruitment and η_{sk} is the wage elasticity of the separation rate to employment. Assuming that the recruitment elasticity equals minus the separation elasticity $\eta_{Rk} = -\eta_{sk}$, the long-term elasticity of labor supply is given by

$$\eta_k = -2\eta_{sk}. \tag{2.4}$$

Thus, under the given assumptions, it is sufficient to estimate the separation rate elasticity in order to obtain an estimate of the labor supply elasticity.[1]

I follow the reduced-form approach of Manning (2013) to estimate separation elasticities for different demographic and skill groups. This observational approach involves relating variation in the wage a worker is paid to the probability that there is an employment separation (e.g. the worker quitting to work for another firm). When the estimated sensitivity is high, a small increase in the wage implies a large decrease in the separation probability. In this case, I infer a high labor supply elasticity and low labor market power of firms. Exploiting the rich structure of the panel data, I condition the analysis on worker-region fixed effects and thereby allow each worker in the sample to have different baseline separations behavior. I exploit the variation in the wage the same worker is paid over time and across different firms within the same region to inform the elasticity. The identifying assumption is that the time variation in individual-level wages is not correlated with unobserved factors affecting whether a worker leaves a firm. The linear specification is given by

$$\text{sep}_{nq} = \delta_{ni} + \delta_q + \delta_j + \sum_a \tilde{\beta_a} \mathbb{1}(nq \in a) \log w_{nq} + \sum_s \tilde{\beta_s} \mathbb{1}(nq \in s) \log w_{nq} + \gamma X_{nq} + \epsilon_{nq} \tag{2.5}$$

where sep_{nq} is an indicator for whether worker n separates from her employer in quarter q, δ_{ni} are worker-region fixed effects, δ_q are quarter fixed effects, δ_j are industry fixed effects and w_{nq} is the individual-level wage. $\mathbb{1}(nq \in a)$ and $\mathbb{1}(nq \in s)$ are indicator functions that take a value of 1 if worker n belongs to age group a and skill group s in quarter q. I define five age groups (20-29,

[1]Note that I abstract from workers changing worker groups. When estimating the model, I use broad age groups such that inflows into age groups and outflows out of age groups are small. I further restrict the sample to workers that do not obtain a university degree after having started to work full-time.

30-39, 40-49, 50-59, 60-64) and two skill groups (workers with and without a college degree). $\tilde{\beta}_a$ and $\tilde{\beta}_s$ are regression coefficients for the demographic group a and the skill group s. X_{nq} is a vector of controls.

The model specified in equation (2.5) might suffer from endogeneity for several reasons. First, the minimum wage introduced in 2015 simultaneously affected wages and separation probabilities. To deal with this issue, I restrict my analysis to job spells from 1994 to 2014. Furthermore, the estimation of heterogeneity in labor supply elasticities might be biased due to compositional differences in age groups. The female labor force participation rate might not be constant across age groups, while several studies have shown that females have a lower labor supply elasticity than males (Barth and Dale-Olsen, 2009; Hirsch et al., 2010). Estimating equation (2.5) might thus suffer from omitted variable bias. Secondly, if the sorting behavior of older workers across sectors and regions differs from the sorting of younger workers, and if labor supply elasticities differ across sectors and regions for other reasons than age, my estimates will be biased. To deal with these endogeneity issues, x_{nq} includes an interaction of log wage with a sector indicator, with a district indicator and with a gender dummy. By including these interactions, I estimate labor supply elasticities across different age groups by comparing older with younger workers of the same gender within the same sector and region.[2]

2.4 Labor supply elasticities over the life cycle

2.4.1 Baseline results

The model specified in equation (2.5) allows me to estimate the effect of age and education on firms' labor market power. The results presented in Table 2.1 reveal that the coefficients are robust across specifications.

For a simpler interpretation of the main coefficients of interest, I follow Manning (2013) and translate $\tilde{\beta}_a + \tilde{\beta}_s$ to an elasticity $\beta_a + \beta_s$ by dividing by the group-specific mean of the outcome. Using equation (2.4), I translate the estimated elasticity of separations to a labor supply elasticity by setting $\eta_k \equiv \eta_{as} = -2(\beta_a + \beta_s)$ where k is the group defined by the interaction of age

[2] I use 15 sectors as defined by Dauth and Eppelsheimer (2021).

Table 2.1: Sensitivity of Worker Turnover
Dependent variable: Separation indicator

	(1)	(2)	(3)	(4)	(5)
log(wage) ×					
age 30-39	0.0568***	0.0577***	0.0579***	0.0568***	0.0563***
	(0.00331)	(0.00340)	(0.00343)	(0.00347)	(0.00347)
age 40-49	0.0753***	0.0765***	0.0768***	0.0756***	0.0750***
	(0.00497)	(0.00508)	(0.00517)	(0.00523)	(0.00524)
age 50-59	0.0795***	0.0806***	0.0810***	0.0798***	0.0793***
	(0.00701)	(0.00712)	(0.00724)	(0.00729)	(0.00730)
age 60-64	0.0738***	0.0749***	0.0753***	0.0742***	0.0738***
	(0.00860)	(0.00869)	(0.00883)	(0.00889)	(0.00889)
college degree		-0.00484***	-0.00478***	-0.00519***	-0.00512***
		(0.000758)	(0.000756)	(0.000750)	(0.000732)
female			0.00456	0.00516	0.00523*
			(0.00281)	(0.00277)	(0.00254)
worker-region FE	yes	yes	yes	yes	yes
industry FE	yes	yes	yes	yes	yes
quarter FE	yes	yes	yes	yes	yes
region-spec. elast.				yes	yes
industry-spec. elast.					yes
R2	.296	.296	.296	.297	.297
N	19610240	19610240	19610240	19610240	19610240

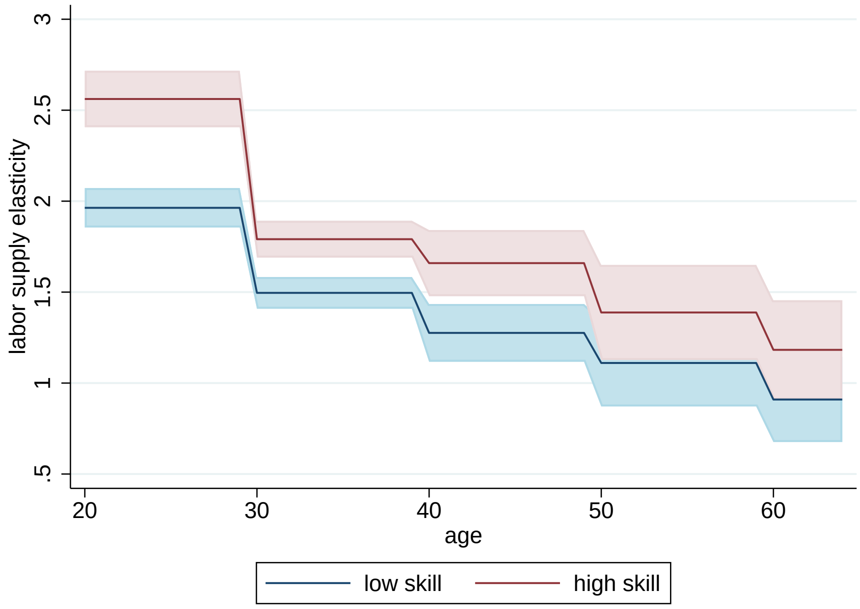
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors in parentheses, clustered at the establishment-quarter level. Male workers at age 20-29 without a college degree are the reference group.

and skill. The estimates of the labor supply elasticity for different skill and demographic groups are plotted in Figure 2.1. While skill does not seem to play a very large role, the labor supply elasticity for the youngest age group is more than twice as large as that for the oldest age group. In terms of the overall magnitude, my results are close to those found in the literature. I find an average elasticity of 1.61 which is very close to the median of 1320 elasticity estimates of 1.68 reported by Sokolova and Sorensen (2021).

Figure 2.2 shows labor supply elasticity estimates from assuming different functional forms in age. The quadratic and the cubic specification reveal that there seems to be a reverting trend around the age of 50: While the

Figure 2.1: Labor supply elasticities across groups



Note: The plot shows the regression results of specification (2) in Table 2.1. The coefficients are transformed into estimates of the labor supply elasticity by dividing by the group-specific mean of the outcome and multiplying with -2. The shaded areas represent 95% confidence intervals.

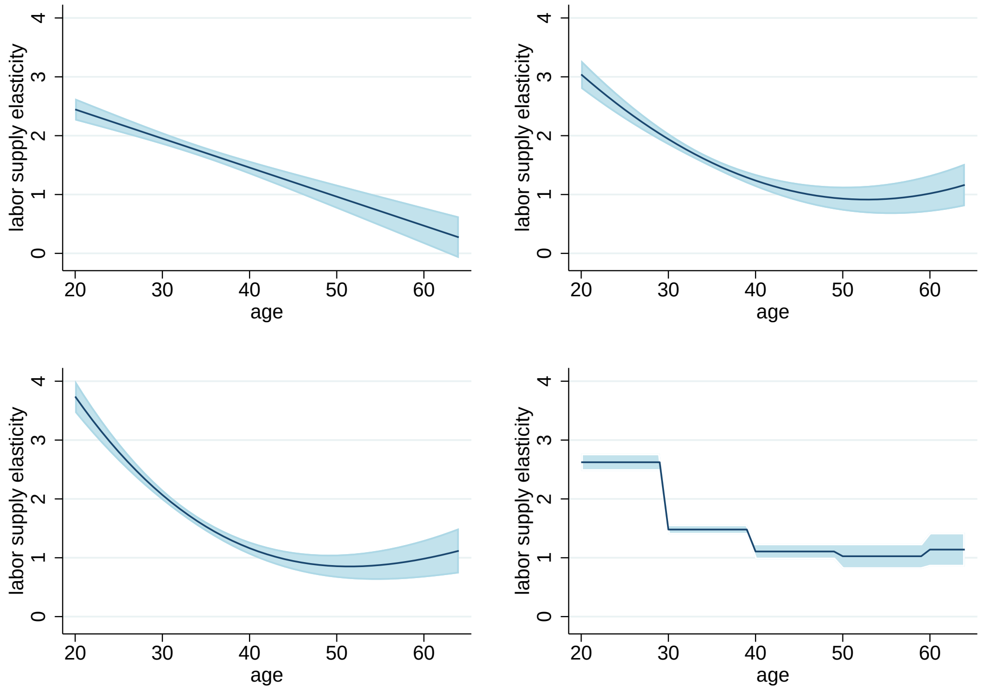
labor supply elasticity is decreasing in age for younger workers, after the age of 50, it is slightly increasing. As my estimation is based on separations into employment and non-employment, the reverting trend likely stems from separations into early retirement. Furthermore, workers close to the retirement age are a selected group since the least attached to the labor market drop out of the labor force earlier.

2.4.2 Robustness checks

As tenure and age are highly correlated, and tenure might affect the labor supply elasticity, my regressions might suffer from omitted variable bias (Manning, 2013). To investigate this problem, I test the robustness of my results to the inclusion of tenure and squared tenure. The estimates presented in Figure 2.3 show a slightly smaller variation in the labor supply elasticity than the baseline results. The pattern of a decreasing elasticity over the life cycle remains however unchanged.

As a further robustness test, I estimate the model in equation (2.5) with

Figure 2.2: Labor supply elasticities from different specifications

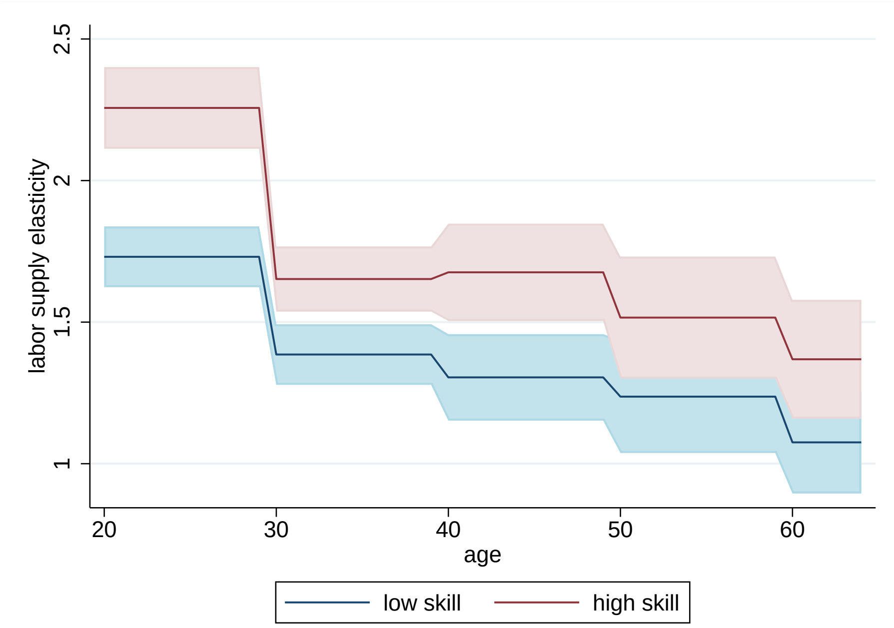


Note: The plot shows estimates of the labor supply elasticity imposing different functional forms in age. The top left plot imposes a linear relation, the top right plot a quadratic relation, the bottom left plot comes from the estimation of a cubic model and the bottom right from estimating group-specific elasticities. The coefficients are transformed into estimates of the labor supply elasticity by dividing by the national mean of the outcome and multiplying with -2. The shaded areas represent 95% confidence intervals.

one skill-coefficient for every age group. The results in Figure 2.4 are similar to the baseline results. They might however suffer from a selection bias in the group of young high skilled workers: The share of workers that graduate from university and start working at a young age is over-represented. I therefore estimate one skill-coefficient for all age-groups in the baseline specification.

In Section 2.4.1, I have addressed the problem of compositional differences in age groups when estimating heterogeneity in labor supply elasticities. If the female labor force participation rate is not constant across age groups and females have a different labor supply elasticity than males, the baseline results might be biased. I have therefore shown that the estimates are robust to controlling for an interaction of log wage with a gender dummy. However, it might be that not only the labor supply elasticity but also the effect of age

Figure 2.3: Labor supply elasticities controlling for tenure



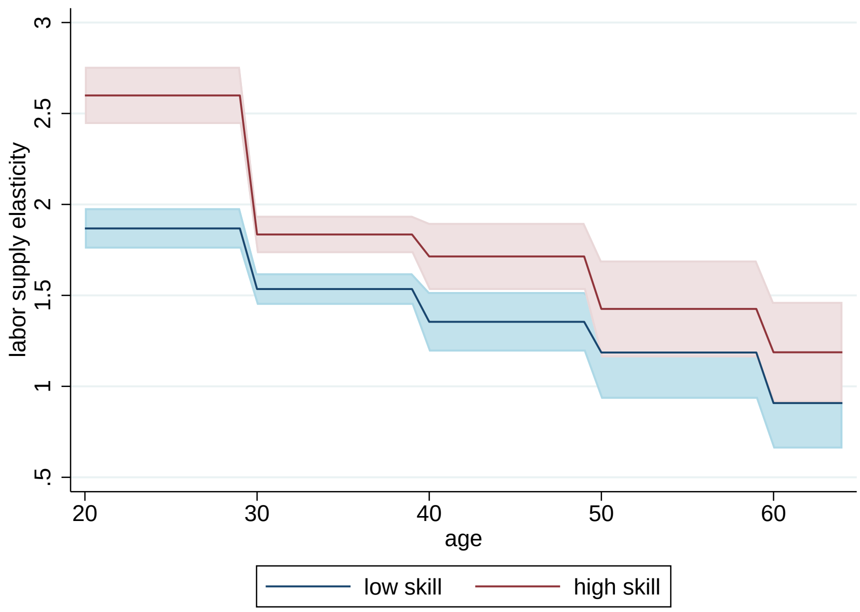
Note: The plot shows estimates of the labor supply elasticity when controlling for tenure, squared tenure and interactions of tenure and squared tenure with the log of wage. The coefficients are transformed into estimates of the labor supply elasticity by dividing by the group-specific mean of the outcome and multiplying with -2. The shaded areas represent 95% confidence intervals.

on the labor supply elasticity differs by gender. To investigate the problem, I estimate the model in equation (2.5) with gender-specific effects of age and skill on the labor supply elasticity. Figure 2.5 shows that there are no significant differences between labor supply elasticities of male and female workers from age 30 to 64.

2.5 Conclusion

Growing literature finds heterogeneity in the degree of labor market power that firms have over different groups of workers. This chapter highlights an often overlooked dimension of heterogeneity in labor market power and empirically documents large differences in labor supply elasticities by age. Using high-quality matched employer-employee data from Germany, I find that firms have more labor market power over older workers, as the labor supply elasticity decreases from more than 2 for the age group 20 to 29 to 1

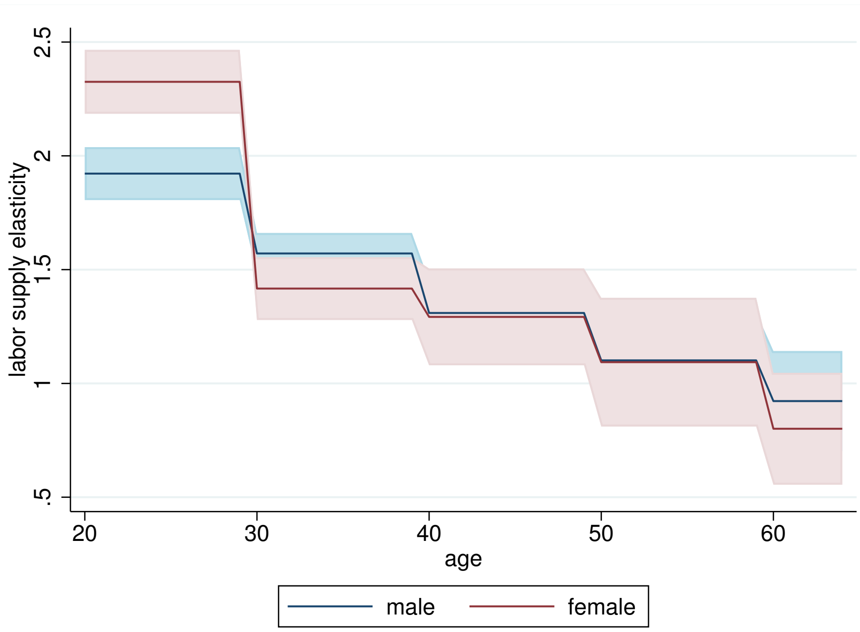
Figure 2.4: Labor supply elasticities for age-skill groups



Note: The plot shows the regression results when estimating the model in equation (2.5) with a separate coefficient for every group defined by the interaction of skill and age. The coefficients are transformed into estimates of the labor supply elasticity by dividing by the group-specific mean of the outcome and multiplying with -2. The shaded areas represent 95% confidence intervals.

for workers aged 60 to 64. My findings highlight the importance of considering demographic factors in understanding labor market power. Furthermore, this study suggests that labor market policies such as minimum wage laws may have differential impacts across age groups. These distributional effects should be taken into account by policymakers.

Figure 2.5: Labor supply elasticities by gender



Note: The plot shows the regression results when estimating the model in equation (2.5) with a separate coefficient for every group defined by the interaction of gender and the age group. The coefficients are transformed into estimates of the labor supply elasticity by dividing by the group-specific mean of the outcome and multiplying with -2. The shaded areas represent 95% confidence intervals.

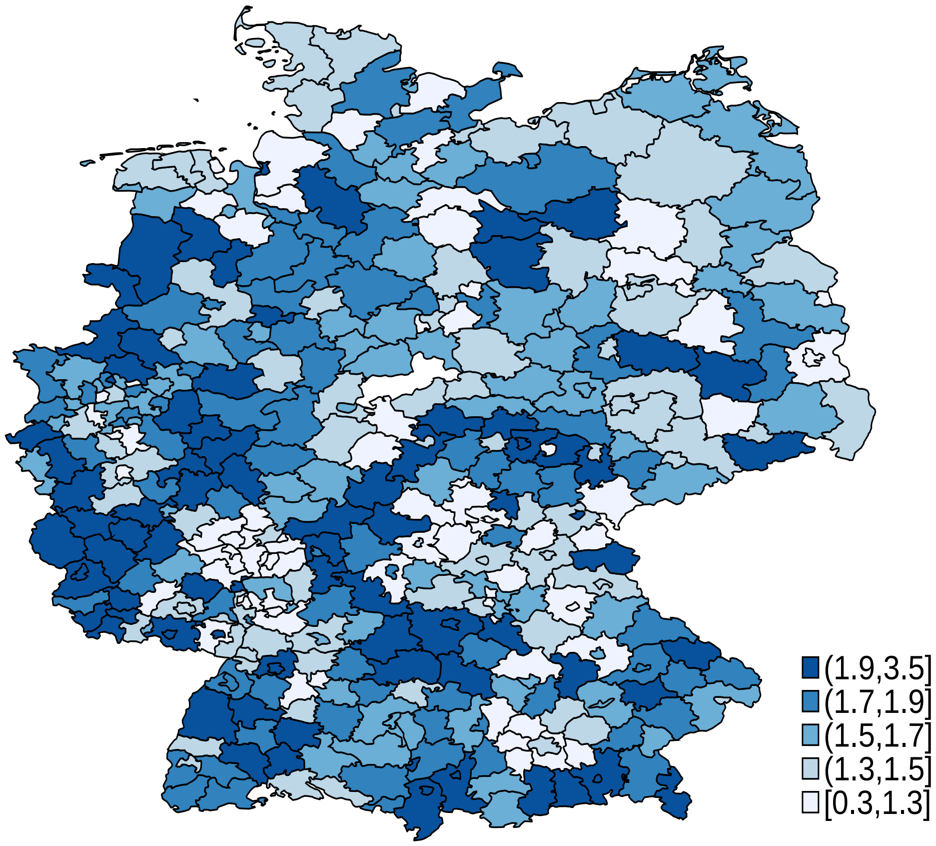
Appendix

Table 2.A.1: Summary Statistics

	mean	p10	p50	p90	sd
separation	.101	0	0	1	.301
wage	107.996	47.701	91.102	178.339	75.262
age	38.703	25	38	54	10.593
college degree	.159	0	0	1	.365
female	.338	0	0	1	.473
N	19 750 740				

Note: The table shows descriptive statistics for the estimation sample that is based on quarterly individual-level data from 1994 to 2014. Wages are gross daily wages.

Figure 2.A.1: Labor supply elasticities across districts



Note: The plot shows the variation in the estimated labor supply elasticities across districts. The estimates are based on the regression results from estimating the model in equation (2.5). The regression coefficients are transformed into estimates of the labor supply elasticity by dividing by the group-specific mean of the outcome and multiplying with -2.

CHAPTER 3

Demographics, Labor Market Power and the Spatial Equilibrium

Chapter Abstract

This chapter studies how demographics affect aggregate labor market power, the urban wage premium and the spatial concentration of population. I develop a quantitative spatial model in which labor market competitiveness depends on the demographic composition of the local workforce. I calibrate the model with reduced-form estimates that indicate that firms have more labor market power over older workers: The labor supply elasticity decreases from more than 2 to 1 from age 20 to 64. I find that differences in labor supply elasticities across age groups can explain 4% of the urban wage premium and 2% of the spatial concentration of population. Demographics and skill together account for 10% of the urban wage premium and 2% of agglomeration.

3.1 Introduction

Increasing wage inequality in many countries has risen concerns of policy makers and the general public alike. While extensive literature has focused on differences in productivity and institutions as key drivers of wage inequality, many dimensions of heterogeneity in labor market power have received little attention in the past (see Katz and Autor (1999) and Acemoglu and Autor (2011) for literature reviews). Recent literature makes clear that there are various reasons for labor market power including not only concentration, but also search frictions, mobility costs, and match-specific amenities, all of which restrict workers' responsiveness to wages (see Card (2022) for an overview). If these factors differ across workers, labor market power has a role to play in explaining wage inequality.

This chapter highlights an often overlooked dimension of heterogeneity in labor market power and empirically analyzes the spatial implications of differences in the sensitivity of worker turnover by age. Given that the age distribution is far from uniform across space, I ask how differences in wage-setting power over demographic groups contribute to spatial wage inequality. To explore the consequences of labor market sorting, I build a spatial general equilibrium model in which labor market competitiveness depends on the demographic composition of the local workforce. I calibrate the key parameters with the reduced-form estimates from Chapter 2. In the model, geographic sorting by age matters and leads to higher labor market power in rural areas, which implies an urban wage premium that is 4% larger than with uniform labor supply elasticities. Heterogeneous labor supply elasticities by age and skill together account for 10% of the urban wage premium. I apply the model to study the effects of the baby boomers retiring. The model predicts that after baby boomers retire, differences in average markdowns between regions decrease by 3%.

To explore the regional implications of differences in the labor supply elasticity across age groups, I develop a spatial general equilibrium model in which labor market competitiveness, as measured by average markdowns, depends on the demographic composition of the local workforce. By doing so, I follow a set of recent papers (see e.g. Bachmann et al., 2021; Ahlfeldt et al., 2022a; Berger et al., 2022) that nest a monopsonistic labor market in a spatial general equilibrium model (Redding and Rossi-Hansberg, 2017). Compared to these studies, I include worker heterogeneity along two dimensions: age and skill. To obtain upward-sloping labor supply curves, I assume that workers draw idiosyncratic tastes for the characteristics of firms. For older workers, different firms are less substitutable due to a larger variation in idiosyncratic taste draws. The assumption of match-specific preferences could capture a variety of more general factors that restrict the mobility of workers in terms of switching employers. As firms have more labor market power over older workers, they face an upward-sloping labor supply curve that is less elastic in regions with an older workforce.

I assume that heterogeneous workers trade off wages, housing costs and regional amenities when making their location decision. By introducing exogenous productivity differences across regions, I allow the model to nest the traditional explanation for wage differences across space. My model further includes exogenous differences in amenities and housing such that it matches spatial data on population and house prices. Different types of workers may vary in how productive they are in each location and in their preference for each location as captured by amenity fundamentals. Firms choose in which labor market to operate in the sense that there is free entry at fixed costs into all locations. Firms combine labor from different worker groups to produce a final good that is traded between regions at zero cost. The production function exhibits increasing returns to scale. I assume that there is a sufficiently large number of firms in each region to rule out strategic wage setting.

How are differences in labor market competitiveness across space sustained in spatial equilibrium? Since workers and firms can freely move between regions, my model formalizes the trade-offs faced by workers and firms when deciding to locate in competitive or less competitive labor markets. In spatial equilibrium, workers enjoy higher wages in competitive locations while paying for it in the form of higher rents or lower amenities. Firms operate at larger scale in competitive locations which allows them to produce profitably despite lower markdowns.

In the model, there is geographic worker sorting due to differences in regional group-specific productivity and amenity fundamentals. Since older and lower skilled workers value rural relative to urban amenities more than younger and higher skilled workers, the share of workers with low labor supply elasticities is larger in rural areas. As a consequence, firms have on average more labor market power in rural areas which gives rise to an urban wage premium. Differences in labor supply elasticities further affect the spatial concentration of population. Since older and lower skilled workers have lower labor supply elasticities, they are also geographically less mobile than younger workers and workers with higher skills.

The model is calibrated to be consistent with the empirically documented reduced-form estimates on labor supply elasticities from Chapter 2. I use the model to quantify the importance of heterogeneity in labor market power for the urban wage premium and the spatial concentration of population. To do so, I counterfactually impose a uniform labor supply elasticity and explore the spatial consequences in general equilibrium. My results suggest that the urban wage premium is 10% lower in a counterfactual scenario in which all workers have the mean labor supply elasticity. Furthermore, I find that differences in labor supply elasticities across worker groups can explain 2% of agglomeration.

The experiment establishes the importance of controlling for differences in age and skill in spatial equilibrium models with monopsonistic competition. I next use the model to estimate the counterfactual of retiring baby boomers. Because demographics matter for labor market power, Germany and other Western economies can expect changes in the national degree of labor market power as well as in its variation across space. As baby boomers will retire in large numbers in the coming decades, labor market power can be expected to decrease in general, but to a larger degree in rural areas. In Germany, the shock might be substantial since the labor force is expected to shrink from roughly 44 million to 33 million until 2060.[1] I find that after baby boomers retire, differences in markdowns between regions decrease by 3%.

This chapter is related to several strands of literature. First, it relates to vast literature on the drivers of wage differences between rural and urban areas. One explanation refers to agglomeration economies, such as increasing returns to scale, labor market pooling, static knowledge spillovers and faster human capital accumulation (see Rosenthal and Strange (2004) for a review).

[1] Forecast from Statistisches Bundesamt (2020c) for a scenario with little immigration, constant labor force participation rates and constant retirement age.

Another strand of literature argues that the urban wage premium is the outcome, at least partially, of workers who are more productive being sorted into dense regions (see e.g. Combes et al., 2008; Moretti, 2013; Diamond, 2016). I provide a new explanation why geographic worker sorting leads to lower wages in rural areas: Firms in these regions possess more labor market power since they face an older workforce that is less mobile in terms of switching workplaces. Geographic worker sorting by age leads to firms offering lower wages in rural areas due to higher labor market power.

My work thereby contributes to an emerging literature on differences in labor market power across regions. Bamford (2021) and Hirsch et al. (2022) find evidence that labor market competitiveness is higher in larger labor markets. However, little research has been done on the drivers of regional differences in labor market power. Bachmann et al. (2021) argue that lower collective wage bargaining coverage in Eastern Germany, by leading to higher monopsony power, can explain the large and persistent wage inequality between East and West Germany. I find that after controlling for age, differences in labor market power between East and West Germany vanish.

A number of recent papers (Azar et al., 2019; Benmelech et al., 2022; Rinz, 2022) finds that wages tend to be lower in highly concentrated labor markets. They conclude that higher concentration is associated with higher labor market power (as in the model of Jarosch et al., forthcoming). Bamford (2021) explains higher labor market power in rural areas with lower competition among potential employers due to a smaller number of firms. I contribute to this literature by focusing on employee-side drivers of wage-setting power rather than employer characteristics. In my setup, there can be labor market power even in the absence of concentration and even with an infinite number of firms.

By analyzing the effects of a changing age composition of the workforce in the context of labor market power, I relate to literature on the labor market effects of population aging. Traditionally, this literature has focused on productivity differences across demographic groups (see National Research Council (2012) for an overview) and productivity changes for all workers due to population aging (Acemoglu and Restrepo, 2021). To the best of my knowledge, this is the first work that studies the wage effects of population aging resulting from changes in average markdowns. Based on an extensive literature survey and own calculations, the National Research Council (2012) concludes that there will be negligible effects of population aging on aggregate productivity over the next two decades. There are however serious difficulties with directly inferring productivity from average real wages as pointed out by Lee (2016).

The labor market effects of demographics have also been studied in the context of technological progress. Acemoglu and Restrepo (2017) find that economies undergoing larger demographic changes have invested significantly more in new robotic and other automation technologies. They argue that this is because ongoing demographic changes are increasing the scarcity of middle-aged workers and industrial automation is most substitutable with middle-aged workers. The overall effect of aging on productivity is ambiguous, but industries with the greatest opportunities for automation are likely to experience more rapid growth in productivity and greater declines in the labor share relative to other industries. Prettner (2013) argues that population aging increases productivity since longer life favors innovation and technology by reducing discount rates and encouraging investment in human capital. On the other hand, lower fertility does impede progress since inventions increase in the number of people they could come from. Rather than focusing on innovation or productivity, I study a different mechanism through which population aging affects labor markets: Since firms have more labor market power over older populations, they face a larger trade-off between growing large and paying low wages such that they decide to remain inefficiently small when facing an old workforce.

The remainder of the chapter is structured as follows. Section 3.2 outlines a quantitative spatial model with monopsonistic competition and different types of workers. A quantitative version of this model is calibrated in Section 3.3. Section 3.4 uses the calibrated model to estimate the effects of demographics on regional differences in labor market power, the urban wage premium and agglomeration. It further analyzes the effects of retiring baby boomers. Section 3.5 concludes.

3.2 Model

In this section, I develop a spatial general equilibrium model with imperfectly competitive local labor markets. I consider an economy that is populated by $L = \sum_k L_k$ workers who I categorize into groups indexed by k (e.g. according to age and skill). Heterogeneous workers choose their employer among firms indexed by f, taking as given the decision of all other individuals. By choosing their employer, workers also choose a region indexed by i. Conditional on their workplace, individuals maximize utility over consumption of housing and tradable goods. Homogeneous firms choose in which labor market to operate (in the sense that there is free entry), they choose profit-maximizing wages for all worker types and produce the final good. Local labor markets vary exogenously in their productivity, amenities, and housing supply.

Following Card et al. (2018), I incorporate monopsonistic labor markets by assuming that firms provide a worker-firm-specific return in the form of an idiosyncratic utility from non-pecuniary job aspects. If the variation in these non-monetary job aspects is large, workers show little sensitivity to wage differences which implies a low labor supply elasticity and a large degree of labor market power. The assumption of match-specific preferences could capture a variety of more general factors that restrict the mobility of workers in terms of switching employers and thereby imply an upward-sloping labor supply curve. Examples are a lack of alternative job offers, incomplete information or moving cost. Since all these factors might differ across demographic and skill groups, I allow the variation in amenity draws to depend on the worker type.

3.2.1 Workers

Preferences of a worker n belonging to group k and being employed by firm f in region i are defined over freely-tradable homogeneous goods c_{ik}, housing h_{ik}, regional amenities E_{ik} and the idiosyncratic amenity shock ϵ_{fn}, according to the Cobb-Douglas form

$$u_{fn} = \left(\frac{c_{ik}}{\alpha}\right)^{\alpha} \left(\frac{h_{ik}}{1-\alpha}\right)^{1-\alpha} E_{ik}\epsilon_{fn}. \tag{3.1}$$

Conditional on working at firm f, a type-k worker solves the following problem:

$$\begin{aligned} v_{fn} &= \max_{c_{ik},h_{ik}} u_{fn} \\ s.t. & \\ c_{ik} + p_i h_{ik} &= w_{ik} \end{aligned} \tag{3.2}$$

where w_{ik} is the wage and p_i is the price of housing. The tradable good is chosen to be the numéraire. Indirect utility is given by

$$v_{fn} = \frac{w_{ik}}{p_i^{1-\alpha}} E_{ik} \epsilon_{fn}. \tag{3.3}$$

I assume that ϵ_{fn} is drawn from a type-1 extreme value distribution which implies closed-form expressions for the number of workers in each firm

$$L_{fk} = \frac{\left(\frac{w_{ik}}{p_i^{1-\alpha}} E_{ik}\right)^{\eta_k}}{\sum_{f'} \left(\frac{w_{i(f')k}}{p_{i(f')}^{1-\alpha}} E_{i(f')k}\right)^{\eta_k}} L_k \tag{3.4}$$

where η_k is inversely related to the shape parameter of the extreme value distribution and captures the extent of preference heterogeneity. Crucially, this parameter differs across demographic groups since older workers are less mobile in terms of switching workplaces. Equation (3.4) gives the upward-sloping labor supply curve of type-k workers to firm f. Firms take the denominator in equation (3.4) as given which can be rationalized by firms being infinitesimally small in relation to the market and other firms not reacting to wage changes of firm f. It follows that η_k is the perceived labor supply elasticity to the firm.

3.2.2 Firms

Identical firms combine labor from different worker groups to produce the freely-traded final good. I assume a linear production function with group- and location-specific productivity shifters A_{ik}. Firms choose wages for every worker type. The firm-level production function of tradable goods exhibits increasing returns to scale due to fixed cost F (expressed in output units).

Firm profits can be written as

$$\Pi_f \quad = \quad Y_f - \sum_k w_{ik} L_{fk}(w_{ik}) - F \tag{3.5}$$

with

$$Y_f \quad = \quad \sum_k A_{ik} L_{fk}(w_{ik}). \tag{3.6}$$

I write $L_{fk}(w_{ik})$ to highlight that the amount of labor a firm employs depends on the wage it pays. Lacking information on the individual realizations of ϵ_{fn}, but knowing the distribution of the shocks, firms take the upward-sloping labor supply curve in equation (3.4) as given and choose w_{ik} to maximize profits. The solution to the profit maximization problem yields classic monopsony wage-setting expressions

$$w_{ik} \quad = \quad \frac{\eta_k}{1+\eta_k} \frac{\partial Y_f}{\partial L_{fk}} \tag{3.7}$$

where $\frac{\eta_k}{1+\eta_k}$ is the markdown and $\frac{\partial Y_f}{\partial L_{fk}} = A_{ik}$ is the marginal revenue product of firm f located in region i. Both the markdown and the marginal revenue product are group-specific. Crucially, the markdown depends on the labor supply elasticity: Because firms have more labor market power over worker groups with a low labor supply elasticity, they pay these worker groups a lower share of their marginal revenue product.

3.2.3 Equilibrium

I assume that firms are homogeneous such that in equilibrium, firms within labor markets pay the same wage, employ the same number of workers and produce the same amount of the tradable good. L_{ik} denotes the total type-k labor supply emerging after households made their decisions, observing w_{ik}, the uniform type-k wage set by all firms in region i. The number of competing firms M_i is determined by free entry. Inserting optimal wage setting (3.7) into firm profits (3.5), setting $\Pi_f = 0$ and imposing the symmetric equilibrium yields

$$Y_i = M_i F + \sum_k L_{ik} \frac{\partial Y_i}{\partial L_{ik}} \frac{\eta_k}{1+\eta_k} \tag{3.8}$$

where $L_{ik} = M_i L_{fk}$ which implies $Y_i = M_i Y_f$. Labor markets clear when equation (3.4) and equation (3.7) hold.

Housing is in fixed supply H_i. The equilibrium price of housing is determined by

$$p_i = (1-\alpha) \frac{\sum_k L_{ik} w_{ik}}{H_i}. \tag{3.9}$$

Profits from the housing sector go to absentee landlords.

Thus, for given fundamentals A_{ik}, E_{ik}, H_i, and parameters F, α and η_k, an equilibrium is a vector of Y_i, M_i, L_{ik}, w_{ik} and p_i for which equations (3.4) and (3.6)-(3.9) hold.

3.3 Quantification

I calibrate the model to German labor market regions in 2017. The quantification of the model consists of two steps. First, I obtain values of the structural parameters. The calibration of the labor supply elasticities η_k is based on the estimates from Chapter 2. Because of data limitations, I use more aggregate age groups than in the reduced-form estimation. I take the housing expenditure share from official statistics for Germany (Statistisches Bundesamt, 2020b). Second, I use data, the calibrated parameter values, and the structure of the model to invert the structural fundamentals A_{ik}, H_i and E_{ik} and fixed cost F.

3.3.1 Data

I estimate the model for the year 2017 on the level of 141 German labor market regions as defined by Kosfeld and Werner (2012) based on commuting data. The areas are constructed by combining one or more districts with the aim of creating self-contained labor markets. The boundaries of local labor markets are defined such that commuting flows between regions are minimized. I drop all regions in which the number of observations for any worker group is smaller than 20. I end up with a sample of 117 labor markets.

I obtain information on regional employment and wages for different worker groups from the individual-level data described in Chapter 2. Based on the results presented in Chapter 2, I split the sample into 4 groups that are defined by the interaction of two skill categories (workers with and without a university degree) and 2 age groups (20-49 years and 50-64 years).[2] I aggregate wages to the labor market level by running the following regression for every worker group k separately:

$$\ln w_n^{raw} = \alpha_k + \beta_k X_n + d_{ik} + \epsilon_n \tag{3.10}$$

where X_n is a set of observable worker characteristics, d_{ik} is a group-region dummy, and ϵ_n is an error term.[3] Given the mincerian regressions, I rescale average wages according to

$$w_{ik} = \exp\left(\alpha_k + \beta_k \frac{1}{L_k} \sum_{n \in k} X_n + d_{ik}\right) \tag{3.11}$$

which represents the average wage of a type-k worker in region i while assuming that workers have otherwise identical characteristics between regions. I calculate the number of firms from the BHP.

I use a house price index from Ahlfeldt et al. (2022b) who utilize data from the FDZ (Forschungsdatenzentrum) Ruhr on real estate offers published on the largest German listing website ImmobilienScout24 with a self-reported market share of about 50% (Klick and Schaffner, 2019). By combining a hedonic regression approach with recent extensions that treat spatial units as the nucleus of a spatial price gradient, Ahlfeldt et al. (2022b) generate an index that controls for property characteristics and distance from the center of the labor market region.

[2] I restrict the sample to workers that do not obtain a university degree after having started to work full-time.

[3] The controls include sex, a dummy that indicates whether a person is German, detailed level of educational attainment, duration of past unemployment periods, and duration of past unemployment periods squared.

Descriptive statistics of the data on the level of labor market regions are shown in Table 3.A.1.

3.3.2 Calibration

I set the housing expenditure share to $1-\alpha = 0.33$, which is in line with the literature (for an overview see Ahlfeldt and Pietrostefani, 2019) and official data from Germany (Statistisches Bundesamt, 2020b). The group-specific labor supply elasticities η_k are obtained by aggregating the estimates presented in Chapter 2. An overview of the calibrated parameters is given in Table 3.1.

Table 3.1: Calibrated Parameters

Parameter	Value
Housing expenditure share	
$1-\alpha$	0.33
Labor supply elasticity (η_k)	
High skilled	
20-49 years	1.88
50-64 years	1.39
Low skilled	
20-49 years	1.59
50-64 years	1.01

Note: The housing expenditure share is taken from official data for Germany (Statistisches Bundesamt, 2020b). The labor supply elasticities are based on the estimation presented in Chapter 2.

I obtain the location-specific productivity, housing supply and amenity shifters A_{ik}, H_i and E_{ik} and fixed cost F by inverting the model so that it exactly matches the observed data on p_i, w_{ik}, L_{ik} and $\sum_i M_i$ for all regions i and worker types k. I start by using equation (3.7) to solve for group- and region-specific productivity fundamentals

$$A_{ik} = w_{ik}\frac{1+\eta_k}{\eta_k}. \tag{3.12}$$

Reformulating equation (3.9) gives an expression for housing fundamentals

$$H_i = (1-\alpha)\frac{\sum_k L_{ik} w_{ik}}{p_i}. \tag{3.13}$$

Fixed cost F can be calculated from equation (3.8). Summing over i and reformulating yields

$$F = \frac{\sum_i \sum_k A_{ik} L_{ik} - \sum_i \sum_k A_{ik} L_{ik} \frac{\eta_k}{1+\eta_k}}{\sum_i M_i}. \tag{3.14}$$

Finally, I solve the mobility constraint in equation (3.4) numerically for the amenity fundamentals E_{ik}

$$L_{ik} = M_i \frac{\left(\frac{w_{ik}}{p_i^{1-\alpha}} E_{ik}\right)^{\eta_k}}{\sum_{f'} \left(\frac{w_{i(f')k}}{p_{i(f')}^{1-\alpha}} E_{i(f')k}\right)^{\eta_k}} L_k \tag{3.15}$$

where I calculate M_i from equation (3.8)

$$M_i = \frac{1}{F}\sum_k L_{ik} A_{ik} - \frac{1}{F}\sum_k \frac{\eta_k}{1+\eta_k} L_{ik} A_{ik}. \tag{3.16}$$

3.4 Model fit and counterfactuals

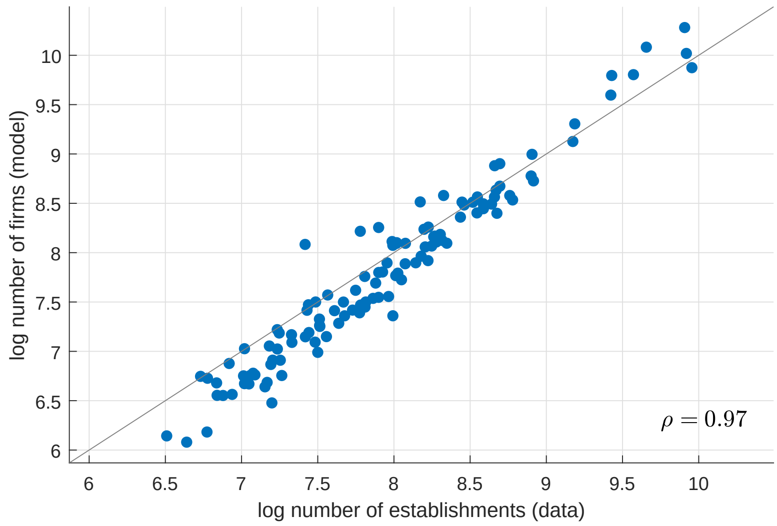
3.4.1 Model vs. data

Since I observe the regional number of establishments in the data, but I only use the mean number of establishments to invert the model, I can evaluate the model fit by comparing the predicted values of M_i with those observed in the data (see Figure 3.1). The predicted number of firms and the actual number of establishments (both in logs) are strongly correlated with a correlation coefficient of 0.97.

3.4.2 Quantitative decomposition

To estimate the effect of demographics on regional differences in labor market power, the urban wage premium and agglomeration, I impose a uniform

Figure 3.1: Predicted number of firms



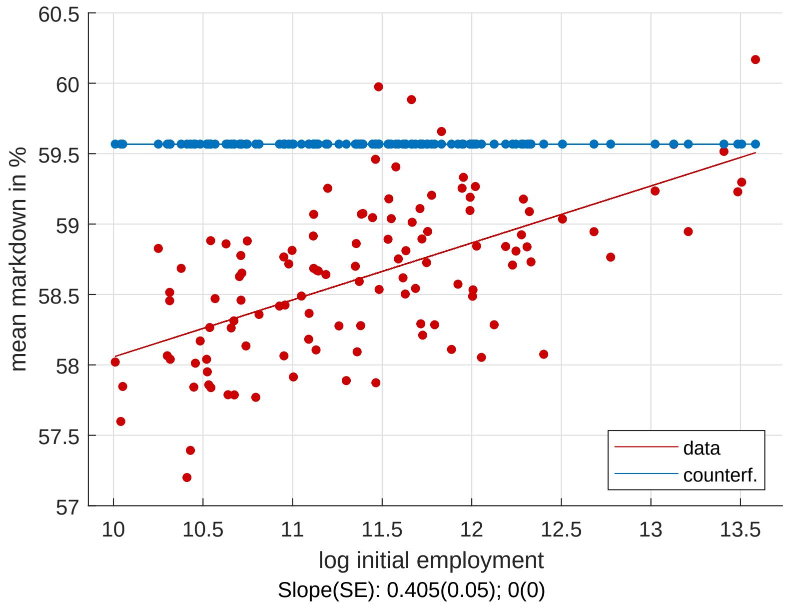
Note: The plot shows the log number of firms as predicted from the model against the log number of establishments observed in the data. Every dot represents one labor market region as defined by Kosfeld and Werner (2012).

labor supply elasticity while leaving all fundamentals and remaining parameters unchanged. Figure 3.2 shows the markdown distribution in the data as compared to a counterfactual in which all workers have the mean labor supply elasticity. Regional average markdowns in the data vary from roughly 57% to 60%. Labor market power is on average significantly smaller in regions with higher employment: Doubling labor market size is associated with an increase in the average markdown of 0.41 percentage points. The counterfactual distribution further shows that a worker with the average elasticity earns roughly 59.5% of her marginal revenue product.

The wage and agglomeration effects of the variation in markdowns across worker groups are illustrated in Figure 3.3. It can be seen that average wages in the counterfactual are higher especially in rural areas. The reason is that the share of old workers with low labor supply elasticities is higher, such that an increase in markdowns has larger effects in rural areas. As a consequence, wages increase more in rural as compared to urban areas which is reflected in a decrease in the urban wage premium of roughly 10%.

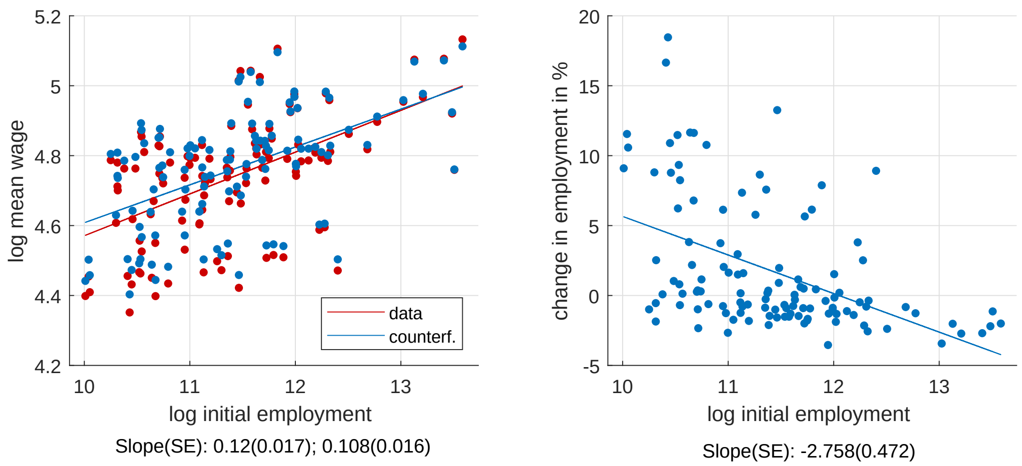
The right panel in Figure 3.3 illustrates the change in employment relative to the observed allocation. Rural areas grow strongly while urban areas shrink. The increase in the labor supply elasticity of old workers implies

Figure 3.2: The markdown distribution



Note: The plot shows markdowns in a counterfactual in which all workers have the mean labor supply elasticity. Markdown is the ratio of wage to the marginal revenue product of labor. Every dot represents one labor market region as defined by Kosfeld and Werner (2012).

Figure 3.3: Wages and agglomeration with uniform markdowns



Note: The plot shows average wages (on the left) and changes in employment (on the right) in a counterfactual in which all workers have the mean labor supply elasticity. Every dot represents one labor market region as defined by Kosfeld and Werner (2012).

a higher mobility in terms of switching jobs which makes old workers geographically more mobile. As old workers have on average a higher expected utility in rural areas, population of old workers in rural areas increases relative to the observed allocation. Young workers, on the other hand, have a lower labor supply elasticity in the counterfactual and are therefore less mobile. Since young workers have a higher utility in urban areas, a decrease in mobility implies an increase in the number of young workers in rural areas. Taking together the mobility responses of all worker groups, I find agglomeration to decline by 2%: The standard deviation of regional employment decreases from 145.1 to 141.8 thousand.

A decomposition of the effects is presented in the third and fourth row of Table 3.2, while the first two rows show the results presented in Figure 3.2 and Figure 3.3. Roughly 60% of the regional variation in markdowns can be explained by demographics alone. Setting the labor supply elasticity to the mean of all worker groups reduces the urban wage premium by 10%, whereby 42% of this decrease is due to differences in demographics.

The last two rows reveal that setting labor supply elasticities for old workers to the level of young workers or vice versa both reduces the regional variation in markdowns and the urban wage premium. An increase in the labor supply elasticity of old workers leads to a decrease in labor market power that is more pronounced in rural areas. As a result, wages in rural areas increase more which leads to a decrease in the urban wage premium. A decrease in the labor supply elasticity of young workers, on the other hand, implies an increase in labor market power that is more pronounced in urban areas. As a result, wages in urban areas decrease more which leads to a decrease in the urban wage premium.

3.4.3 The effects of retiring baby boomers

I model the shock of retiring baby boomers as a national change in the size of the different worker groups. I use the population projection from Statistisches Bundesamt (2020a) because the labor force participation forecast (Statistisches Bundesamt, 2020c) is only available for aggregated age groups different from the groups that I define. I choose the forecast for a scenario with moderate changes in fertility and moderate immigration. The projection is not available for different skill groups, which is why I assume population in both skill groups to change to the same extent. According to the popula-

Table 3.2: Decomposition of Regional Wage and Population Differences

counterfactual elasticity				markdowns	urban wage	agglomeration
low skill		high skill			premium	
young	old	young	old			
$\eta_{low,young}$	$\eta_{low,old}$	$\eta_{high,young}$	$\eta_{high,old}$	0.405 (0.050)	0.120 (0.017)	145.1
$\bar{\eta}$				0 (0)	0.108 (0.016)	141.8
$\bar{\eta}_{low}$		$\bar{\eta}_{high}$		0.242 (0.026)	0.115 (0.016)	142.3
$\bar{\eta}_{young}$	$\bar{\eta}_{old}$	$\bar{\eta}_{young}$	$\bar{\eta}_{old}$	0.190 (0.043)	0.114 (0.017)	144.4
$\eta_{low,young}$		$\eta_{high,young}$		0.206 (0.022)	0.116 (0.017)	138.8
$\eta_{low,old}$		$\eta_{high,old}$		0.283 (0.031)	0.111 (0.016)	139.2

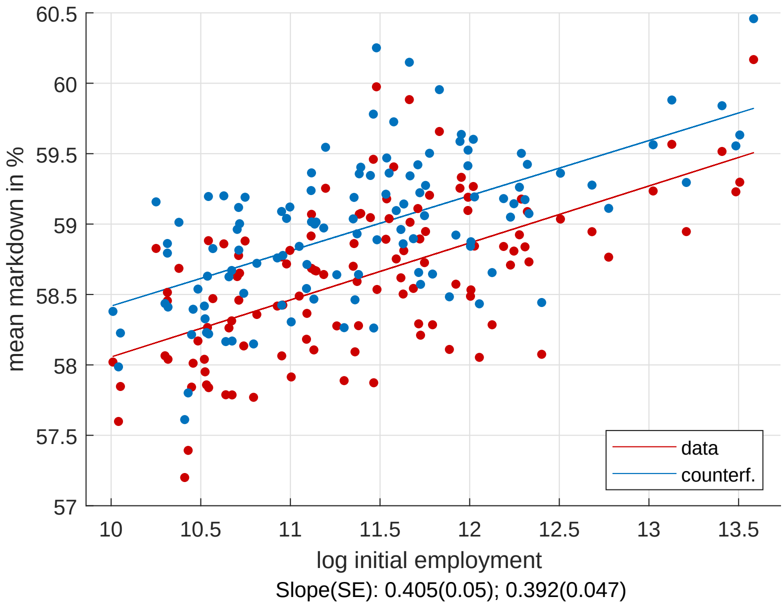
Note: Standard errors in parentheses. The table shows regression results with an intercept and log initial employment as explanatory variables. Dependent variables are markdowns (in %) in column 5 and log average wage in column 6. The last column lists the standard deviation of employment (in thousand). $\bar{\eta}, \bar{\eta}_{low}, \bar{\eta}_{high}, \bar{\eta}_{young}$ and $\bar{\eta}_{old}$ are population-weighted average elasticities.

tion projection from Statistisches Bundesamt (2020a), the age group 20-49 is expected to shrink by 12.5% and the age group 50-64 is expected to shrink by 25.6% until 2060.

Figure 3.4 plots the markdown distribution observed in the data as compared to the counterfactual distribution. After baby boomers retire, average labor market power decreases which is why workers receive a larger share of their marginal revenue product as reflected in 0.4 percentage point higher average markdowns. The slope parameter decreases slightly (by 3%) since the share of older workers is larger in rural areas.

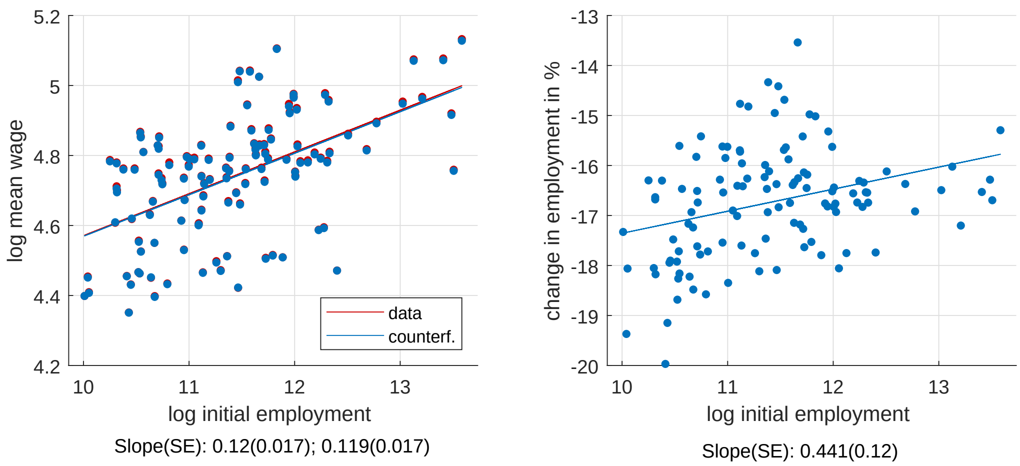
The left part of Figure 3.5 plots observed and counterfactual log wages against region size. In the model, the shock to the relative size of the different age groups leads to changes in regional wage inequality and the spatial distribution of economic activity. The urban wage premium slightly decreases after the shock as labor market power in rural areas decreases more than in urban areas (Figure 3.4). The decrease in population is larger in rural areas (see the right plot of Figure 3.5) since the share of retiring workers is larger

Figure 3.4: Markdowns after baby boomers retire



Note: The plot shows the markdown distribution in the counterfactual of retiring baby boomers. Markdown is the ratio of wage to the marginal revenue product of labor. Every dot represents one labor market region as defined by Kosfeld and Werner (2012).

Figure 3.5: Wages and agglomeration after baby boomers retire



Note: The plot shows wages and agglomeration in the counterfactual of retiring baby boomers. Every dot represents one labor market region as defined by Kosfeld and Werner (2012).

in these areas.

3.5 Conclusion

Labor economists are increasingly questioning the assumption of almost perfectly competitive labor markets, they spend increasing efforts on estimating the degree of labor market power and its impact on inequality (Manning, 2013; Card, 2022). I contribute to this growing debate by quantifying the effect of differences in labor market power across worker groups on regional inequality. In Chapter 2, I show that firms have significantly more wage-setting power over older and lower skilled workers. In this chapter, I build a spatial general equilibrium model with monopsonistic labor markets and estimate that differences in markdowns across worker groups can explain 10% of the urban wage premium and 2% of agglomeration.

While the model shows how demographics affect labor market power, the urban wage premium and agglomeration, one fundamental question remains open for future research: What are the policy implications of (differences in) labor market power? The answer to this question depends on the fundamental forces underlying differences in labor mobility. Traditional theory suggests that firms who set a relatively high markdown are under-producing, from a social welfare perspective. However, if low labor mobility is the result of switching costs or non-pecuniary amenities, setting incentives for workers to switch employers might not be optimal from a social planner perspective. The policy implications might be different if labor market power results from information frictions (as in Jäger et al., forthcoming).

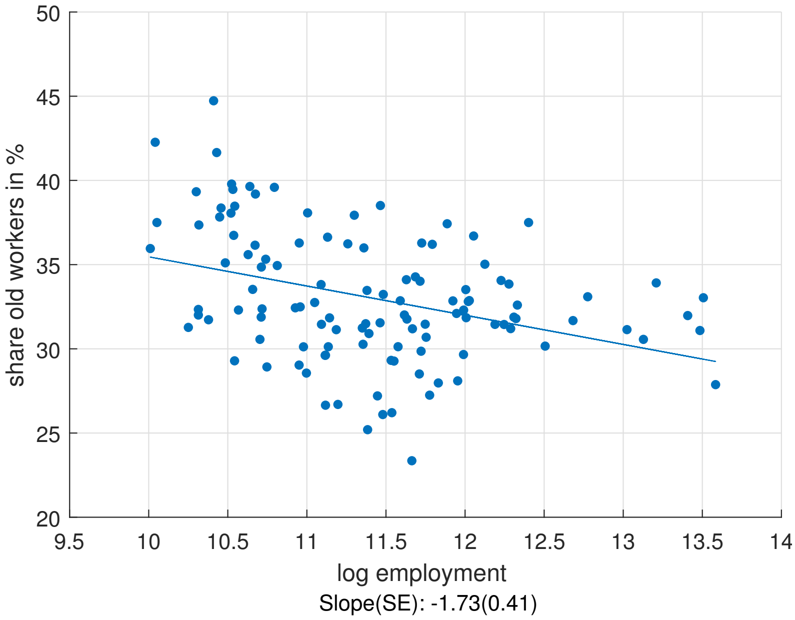
Appendix

Table 3.A.1: Summary Statistics

	mean	sd	min	max
Low skilled				
age 20-49				
wage	90.354	10.231	71.027	110.677
employment (in thd)	68.652	67.754	11.700	362.800
age 50-64				
wage	95.128	11.782	73.604	115.164
employment (in thd)	33.294	32.743	6.850	173.750
High skilled				
age 20-49				
wage	153.716	20.218	107.314	204.998
employment (in thd)	19.992	33.826	1.300	230.600
age 50-64				
wage	178.956	29.401	111.978	231.096
employment (in thd)	8.645	13.095	1.100	75.550
House purchase price	1	.562	.323	4.371
No. of establishments (in thd)	3.819	3.833	.671	21.059

Note: The table shows descriptive statistics for 117 labor markets as defined by Kosfeld and Werner (2012) in 2017. Wages are gross daily wages, house prices are relative to the national mean.

Figure 3.A.1: Demographics across districts



Note: The plot shows the share of workers in the age group 50 to 64 (relative to workers aged 20 to 64). Every dot represents one labor market region as defined by Kosfeld and Werner (2012).

Bibliography

Acemoglu, Daron and David Autor, "Chapter 12 - Skills, Tasks and Technologies: Implications for Employment and Earnings," *Handbook of Labor Economics*, 2011, *4*, 1043–1171.

_ **and Pascual Restrepo**, "Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation," *American Economic Review*, 2017, *107* (5), 174–79.

_ **and** _ , "Demographics and Automation," *The Review of Economic Studies*, 2021, *89* (1), 1–44.

Ahlfeldt, Gabriel and Elisabetta Pietrostefani, "The economic effects of density: A synthesis," *Journal of Urban Economics*, 2019, *111*, 93–107.

_ **, Duncan Roth, and Tobias Seidel**, "Optimal Minimum Wages," *CEPR Press Discussion Paper*, 2022, *16913.*

_ **, Stephan Heblich, and Tobias Seidel**, "Micro-geographic property price and rent indices," *Regional Science and Urban Economics*, 2022, p. 103836.

Albouy, David, "The Unequal Geographic Burden of Federal Taxation," *Journal of Political Economy*, 2009, *117* (4), 635–667.

_ **, Gabriel Ehrlich, and Yingyi Liu**, "Housing Demand, Cost-of-Living Inequality, and the Affordability Crisis," *National Bureau of Economic Research*, 2016, *22816.*

Antoni, Manfred, Philipp vom Berge, Tobias Graf, Stephan Grießemer, Steffen Kaimer, Markus Köhler, Claudia Lehnert, Martina Oertel, Alexandra Schmucker, Stefan Seth, and Christan Seysen, "Weakly anonymous Version of the Sample of Integrated Labour Market Biographies (SIAB) – Version 7517 v1," *Unpublished report*, 2019.

Azar, José, Steven Berry, and Ioana Elena Marinescu, "Estimating Labor Market Power," *Available at SSRN 3456277*, 2019.

Bachmann, Rüdiger, Christian Bayer, Heiko Stüber, and Felix Wellschmied, "Monopsony Makes Firms not only Small but also Unproductive: Why East Germany has not Converged," *Unpublished paper*, 2021.

Bamford, Iain, "Monopsony Power, Spatial Equilibrium, and Minimum Wages," *Unpublished paper*, 2021.

Barth, Erling and Harald Dale-Olsen, "Monopsonistic discrimination, worker turnover, and the gender wage gap," *Labour Economics*, 2009, *16* (5), 589–597.

Baum-Snow, Nathaniel and Ronni Pavan, "Inequality and City Size," *The Review of Economics and Statistics*, 2013, *95* (5), 1535–1548.

Benmelech, Efraim, Nittai Bergman, and Hyunseob Kim, "Strong Employers and Weak Employees How Does Employer Concentration Affect Wages?," *Journal of Human Resources*, 2022, *57*, 200–250.

Berger, David, Kyle Herkenhoff, and Simon Mongey, "Labor Market Power," *American Economic Review*, 2022, *112* (4), 1147–93.

Bornstein, Gideon, "Entry and Profits in an Aging Economy: The Role of Consumer Inertia," *Review of Economic Studies*, forthcoming.

Burdett, Kenneth and Dale T. Mortensen, "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, 1998, *39* (2), 257–273.

Card, David, "Who Set Your Wage?," *American Economic Review*, 2022, *112* (4), 1075–90.

__ , Ana Rute Cardoso, Joerg Heining, and Patrick Kline, "Firms and Labor Market Inequality: Evidence and Some Theory," *Journal of Labor Economics*, 2018, *36* (1), 13–70.

Colas, Mark and Kevin Hutchinson, "Heterogeneous Workers and Federal Income Taxes in a Spatial Equilibrium," *American Economic Journal: Economic Policy*, 2021, *13* (2), 100–134.

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

_ , _ , and _ , "The Costs of Agglomeration: House and Land Prices in French Cities," *Review of Economic Studies*, 2019, *86* (4), 1556–1589.

Couture, Victor, Cecile Gaubert, Jessie Handbury, and Erik Hurst, "Income Growth and the Distributional Effects of Urban Spatial Sorting," *Review of Economic Studies*, forthcoming.

Dauth, Wolfgang and Johann Eppelsheimer, "Preparing the sample of integrated labour market biographies (SIAB) for scientific analysis: a guide," *Journal for Labour Market Research*, 2021, *54* (1), 1–14.

Davis, Morris A. and François Ortalo-Magné, "Household expenditures, wages, rents," *Review of Economic Dynamics*, 2011, *14* (2), 248–261.

Delventhal, Matthew J., Eunjee Kwon, and Andrii Parkhomenko, "JUE Insight: How do cities change when we work from home?," *Journal of Urban Economics*, 2022, *127*, 103331.

Diamond, Rebecca, "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000," *American Economic Review*, 2016, *106* (3), 479–524.

_ and Cecile Gaubert, "Spatial Sorting and Inequality," *Annual Review of Economics*, 2022, *14* (1), 795–819.

Eckert, Fabian, Sharat Ganapati, and Conor Walsh, "Skilled Scalable Services: The New Urban Bias in Economic Growth," *Available at SSRN 3736487*, 2020.

Eeckhout, Jan, Roberto Pinheiro, and Kurt Schmidheiny, "Spatial Sorting," *Journal of Political Economy*, 2014, *122* (3), 554–620.

Engbom, Niklas, "Firm and Worker Dynamics in an Aging Labor Market," *Federal Reserve Bank of Minneapolis Discussion Paper*, 2019, *756.*

Fajgelbaum, Pablo D. and Cecile Gaubert, "Optimal Spatial Policies, Geography, and Sorting," *The Quarterly Journal of Economics*, 2020, *135* (2), 959–1036.

__ , Eduardo Morales, Juan Carlos Suárez Serrato, and Owen Zidar, "State Taxes and Spatial Misallocation," *The Review of Economic Studies*, 2018, *86* (1), 333–376.

Finlay, John and Trevor Williams, "Sorting and the Skill Premium: The Role of Nonhomothetic Housing Demand," *Journal of International Economics*, forthcoming.

Furbach, Nina, "Demographics, Labor Market Power and the Spatial Equilibrium," *Ruhr Economic Papers*, 2023, *998.*

Ganong, Peter and Daniel Shoag, "Why has regional income convergence in the US declined?," *Journal of Urban Economics*, 2017, *102*, 76–90.

Gaubert, Cecile, Patrick M. Kline, and Danny Yagan, "Place-Based Redistribution," *American Economic Review*, forthcoming.

Giannone, Elisa, "Skilled-Biased Technical Change and Regional Convergence," *Journal of Political Economy*, forthcoming.

Gupta, Arpit, Vrinda Mittal, Jonas Peeters, and Stijn Van Nieuwerburgh, "Flattening the curve: Pandemic-Induced revaluation of urban real estate," *Journal of Financial Economics*, 2022, *146* (2), 594–636.

Gyourko, Joseph, Christopher Mayer, and Todd Sinai, "Superstar Cities," *American Economic Journal: Economic Policy*, 2013, *5* (4), 167–99.

Hirsch, Boris and Elke J. Jahn, "Is There Monopsonistic Discrimination against Immigrants?," *ILR Review*, 2015, *68* (3), 501–528.

__ , Elke J Jahn, Alan Manning, and Michael Oberfichtner, "The Urban Wage Premium in Imperfect Labor Markets," *Journal of Human Resources*, 2022, *57*, 111–136.

__ , Thorsten Schank, and Claus Schnabel, "Differences in Labor Supply to Monopsonistic Firms and the Gender Pay Gap: An Empirical Analysis

Using Linked Employer-Employee Data from Germany," *Journal of Labor Economics*, 2010, *28* (2), 291–330.

Hopenhayn, Hugo, Julian Neira, and Rish Singhania, "From Population Growth to Firm Demographics: Implications for Concentration, Entrepreneurship and the Labor Share," *Econometrica*, 2022, *90* (4), 1879–1914.

Jarosch, Gregor, Jan Sebastian Nimczik, and Isaac Sorkin, "Granular Search, Market Structure, and Wages," *Review of Economic Studies*, forthcoming.

Jäger, Simon, Christopher Roth, Nina Roussille, and Benjamin Schoefer, "Worker Beliefs About Outside Options," *Quarterly Journal of Economics*, forthcoming.

Karahan, Fatih, Benjamin Pugsley, and Ayşegül Şahin, "Demographic Origins of the Startup Deficit," *American Economic Review*, forthcoming.

Katz, Lawrence and David Autor, "Chapter 26 - Changes in the Wage Structure and Earnings Inequality," *Handbook of Labor Economics*, 1999, *3*, 1463–1555.

Klick, Larissa and Sandra Schaffner, "FDZ data description: Regional real estate price indices for Germany (RWI-GEO-REDX)," *RWI Projektberichte*, 2019.

Kosfeld, Reinhold and Alexander Werner, "Deutsche Arbeitsmarktregionen-Neuabgrenzung nach den Kreisgebietsreformen 2007-2011," *Raumforschung und Raumordnung*, 2012, *70* (1), 49–64.

Lee, Ronald, "Chapter 2 - Macroeconomics, Aging, and Growth," *Handbook of the Economics of Population Aging*, 2016, *1*, 59–118.

Liang, James, Hui Wang, and Edward P. Lazear, "Demographics and Entrepreneurship," *Journal of Political Economy*, 2018, *126* (1), 140–196.

Manning, Alan, *Monopsony in Motion: Imperfect Competition in Labor Markets*, Princeton University Press, 2013.

Moretti, Enrico, *The New Geography of Jobs*, Houghton Mifflin Harcourt, 2012.

—, "Real Wage Inequality," *American Economic Journal: Applied Economics*, 2013, *5* (1), 65–103.

National Research Council, *Aging and the Macroeconomy: Long-Term Implications of an Older Population*, Washington, DC: The National Academies Press, 2012.

OECD, "Housing prices (indicator)," *Accessed on 08 December 2022*, 2022.

Ossa, Ralph, "A Quantitative Analysis of Subsidy Competition in the U.S.," *Journal of Public Economics*, forthcoming.

Prettner, Klaus, "Population aging and endogenous economic growth," *Journal of Population Economics*, 2013, *26* (2), 811–834.

Redding, Stephen J. and Esteban Rossi-Hansberg, "Quantitative Spatial Economics," *Annual Review of Economics*, 2017, *9* (1), 21–58.

Rinz, Kevin, "Labor Market Concentration, Earnings, and Inequality," *Journal of Human Resources*, 2022, *57*, 251–283.

Rosenthal, Stuart S. and William C. Strange, "Chapter 49 - Evidence on the Nature and Sources of Agglomeration Economies," *Handbook of Regional and Urban Economics*, 2004, *4*, 2119–2171.

Rossi-Hansberg, Esteban, Pierre-Daniel Sarte, and Felipe Schwartzman, "Cognitive Hubs and Spatial Redistribution," *NBER Working Paper*, 2019, *26267*.

Rubinton, Hannah, "The Geography of Business Dynamism and Skill Biased Technical Change," *Review of Economic Studies*, forthcoming.

Schaeffer, Katherine, "Key facts about housing affordability in the U.S.," *Pew Research Center, Unpublished report*, 2022.

Sokolova, Anna and Todd Sorensen, "Monopsony in Labor Markets: A Meta-Analysis," *ILR Review*, 2021, *74* (1), 27–55.

Statistisches Bundesamt, "Preise - Verbraucherpreisindizes für Deutschland," *Unpublished report*, 2019.

—, "Bevölkerungsvorausberechnung," *Unpublished report*, 2020.

—, "Einkommens- und Verbrauchsstichprobe Konsumausgaben privater Haushalte," *Fachserie*, 2020, *15* (5).

—, "Erwerbspersonenvorausberechnung," *Unpublished report*, 2020.