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Nina Furbach Demographics, labor market power
and the spatial equilibrium

Abstract

This paper 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. Using highly disaggregated administrative data from Germany, I find 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. Calibrating the model with the reduced-form elasticity estimates, 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.

Non-technical summary

Increasing wage inequality in many Western economies 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 paper contributes to the literature on differences in labor market power by analyzing a new dimension of heterogeneity: demographics. Since older workers are less mobile in terms of switching workplaces, firms have more labor market power over older workers. 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.

I start by estimating labor market power by measuring the sensitivity of worker turnover to the wage paid. To do so, I run individual-level regressions on high-quality matched employer-employee data from German social security records covering the years 1994 to 2017. 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.

Next, I provide 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 to the firm 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 mechanism analyzed in this 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).

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 model to be consistent with the empirically documented reduced-form estimates on labor supply elasticities by worker group. I estimate the model on the level of 141 labour market regions in Germany in 2017. The model is inverted to exactly match data on regional wages and employment for different age and skill groups and regional house prices. My model provides evidence that geographic sorting by age and skill matters and leads to higher labor market power in rural areas, which implies an urban wage premium that is 10% larger than with uniform labor supply elasticities. 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 have differential impacts across age and skill groups and across regions. These distributional effects should be taken into account by policymakers.

1 Introduction

Increasing wage inequality in many Western economies 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 paper highlights an often overlooked dimension of heterogeneity in labor market power and empirically documents large 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. 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%.

My findings suggest that the age composition of the workforce, by affecting labor market power, plays an important role in explaining regional wage differences. 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.

Motivated by the theoretical channels, I start by empirically estimating the degree of la-

bor market power for different demographic and skill groups. I utilize high-quality matched employer-employee data from Germany for the years 1994 to 2014 (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.

To explore the regional implications of differences in the labor supply elasticity, 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 are free to move between labor markets, my model formalizes the tradeoffs faced by workers and firms when deciding whether to locate in competitive or less-competitive labor markets. In spatial equilibrium, workers enjoy higher wages in high-competitiveness locations while paying for it in the form of higher rents or lower amenities. Firms operate at larger scale in high-competitiveness locations, allowing 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. 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 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 paper is related to several strands of literature. First, it is related to emerging literature on the effects 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 quantify the regional implications of population aging.

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.

My paper is further related to a vast literature that estimates labor supply elasticities for different groups of workers. There is literature showing that the labor supply elasticity is lower for women (Barth and Dale-Olsen, 2009; Hirsch et al., 2010) and migrants (Hirsch and Jahn, 2015). 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

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

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). I focus, however, 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. I offer an alternative explanation why labor market power differs across regions: Since denser regions have a younger workforce, workers are more mobile in terms of switching jobs which implies lower labor market power of firms.

The remainder of the paper is structured as follows. Section 2 estimates labor supply elasticities for different age and skill groups. Section 3 outlines a quantitative spatial model with monopsonistic competition and different types of workers. A quantitative version of this model is calibrated in Section 4. Section 5 uses the calibrated model to estimate the effects of demographics on regional differences in labor market power, the urban wage premium and agglomeration. Section 6 analyzes the effects of retiring baby boomers, and Section 7 concludes.

2 Estimating age-specific labor supply elasticities

2.1 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 1994 to 2017 (Antoni et al., 2019).[2] 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.

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[2]I drop the years before 1994 because data from East Germany is not available before 1991 and is incomplete up to 1993.

2.2 Method

I estimate labor supply elasticities for different demographic and skill groups. Using a canonical approach from the labor literature on monopsony, I estimate the elasticity of labor supply that firms face by measuring the sensitivity of worker turnover to the wage paid (Manning, 2013; Hirsch et al., 2022). This observational approach involves relating variation in the wage a worker is paid to the probability that there is an employment separation (for example, 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

$$\mathrm{sep}_{nq} = \delta_{ni} + \delta_q + \delta_j + \sum_a \tilde{\beta}_a \mathbb{1}(nq \in a) \log w_{nq} + \sum_s \tilde{\beta}_s \mathbb{1}(nq \in s) \log w_{nq} + \gamma X_{nq} + \epsilon_{nq} \tag{1}$$

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, 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 (1) 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 (1) 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.[3]

2.3 Results

The model specified in equation (1) allows me to estimate the effect of age and education on firms' labor market power. The results presented in Table 1 reveal that the coefficients are robust across specifications.

For a simpler interpretation of the coefficients, 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. 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 and skill.[4] The estimates of the labor supply elasticity for different skill and demographic groups are plotted in Figure 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 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 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

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

[4] Note that the transformation is based on the assumption that the recruitment elasticity equals minus the separation elasticity. Since the labor supply elasticity to the firm η_k can be written as the difference of the wage elasticity of recruitment η_{Rk} and the wage elasticity of the separation rate $\beta_a + \beta_s$, I get $\eta_k = \eta_{Rk} - (\beta_a + \beta_s) = -2(\beta_a + \beta_s)$ (Manning, 2013).

Table 1: Sensitivity of Worker Turnover

Dependent variable: Separation indicator

|	(1)	(2)	(3)	(4)	(5)
log(wage) $\times$					
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-specific elasticity				yes	yes
industry-specific elasticity					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.

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. In Section A.3, I show that the results are robust to the inclusion of tenure and the estimation of skill-specific age coefficients.

3 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

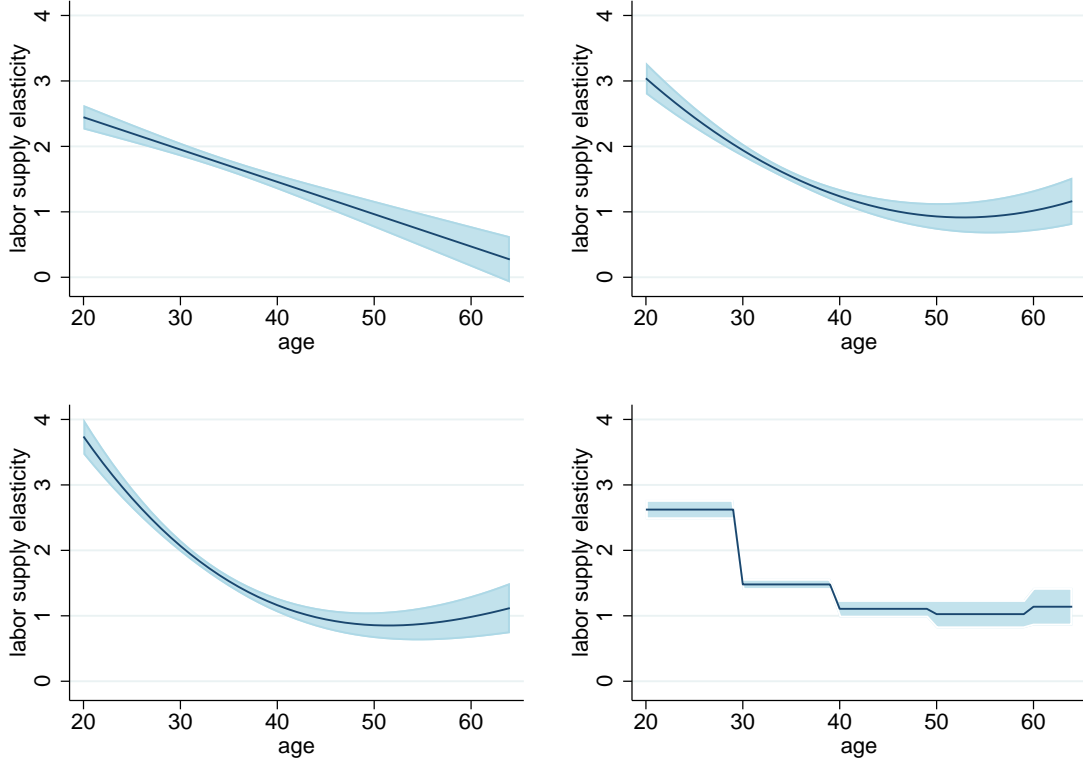Figure 1: Labor supply elasticities across groups
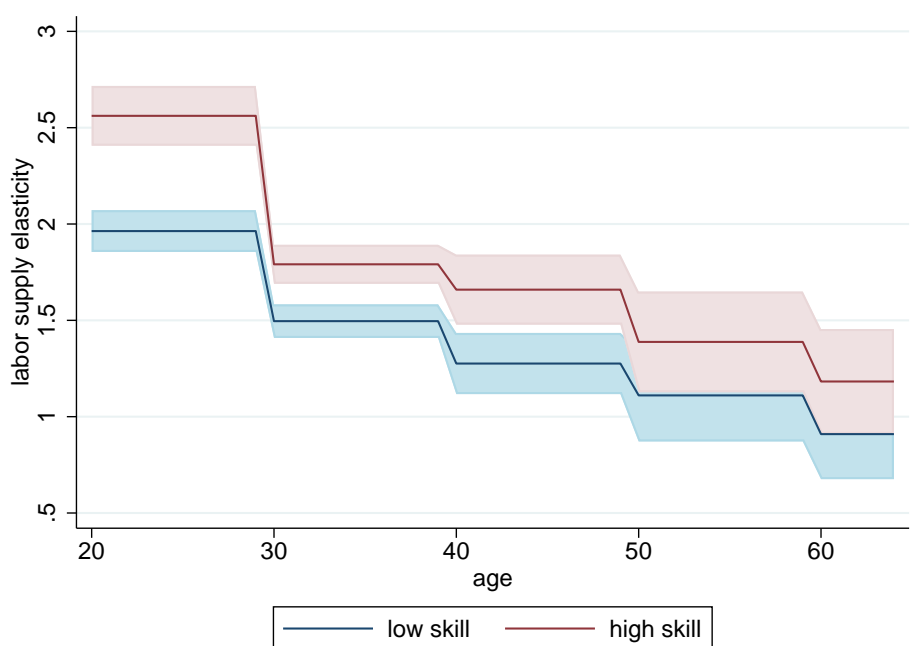
Note: The plot shows the regression results of specification (2) in Table 1. The coefficients are transformed into estimates of the labor supply elasticity by dividing by the group-specific mean of the outcome and multiplying with -2. The shaded areas represent 95% confidence intervals.

choosing their employer, workers also choose a region indexed by i. Conditional on their workplace, workers 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.

Figure 2: Labor supply elasticity estimates 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.

3.1 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

$$u_{fn} = \left(\frac{c_{ik}}{\alpha}\right)^{\alpha}\left(\frac{h_{ik}}{1-\alpha}\right)^{1-\alpha} E_{ik}\epsilon_{fn}. \tag{2}$$

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

$$
\begin{aligned}
v_{fn} &= \max_{c_{ik},h_{ik}} u_{fn} \\
s.t. & \\
c_{ik} + p_i h_{ik} &= w_{ik}
\end{aligned}
\tag{3}
$$

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

$$v_{fn} = \frac{w_{ik}}{p_i^{1-\alpha}} E_{ik} \epsilon_{fn}. \tag{4}$$

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

$$L_{fk} = \frac{\left(\frac{w_{ik}}{p_i^{1-\alpha}} E_{ik}\right)^{\eta_k}}{\sum_{f'} \left(\frac{w_{i(f')k}}{p_{i(f')}^{1-\alpha}} E_{i(f')k}\right)^{\eta_k}} L_k \tag{5}$$

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 (5) gives the upward-sloping labor supply curve of type k workers to firm f. Firms take the denominator in equation (5) 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 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

$$\Pi_f = Y_f - \sum_k w_{ik} L_{fk}(w_{ik}) - F \tag{6}$$

with

$$Y_f = \sum_k A_{ik} L_{fk}(w_{ik}). \tag{7}$$

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 realisations of ϵ_{fn}, but knowing the distribution

of the shocks, firms take the upward-sloping labor supply curve in equation (5) as given and choose w_{ik} to maximize profits. The solution to the profit maximization problem yields classic monopsony wage-setting expressions

$$w_{ik} = \frac{\eta_k}{1+\eta_k}\frac{\partial Y_f}{\partial L_{fk}} \tag{8}$$

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.

3.3 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 (8) into firm profits (6), setting $\Pi_f = 0$ and imposing the symmetric equilibrium yields

$$Y_i = M_i F + \sum_k L_{ik}\frac{\partial Y_i}{\partial L_{ik}}\frac{\eta_k}{1+\eta_k} \tag{9}$$

where $L_{ik} = M_i L_{fk}$ which implies $Y_i = M_i Y_f$. Labor makets clear when equation (5) and equation (8) hold.

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

$$p_i = (1-\alpha)\frac{\sum_k L_{ik} w_{ik}}{H_i}. \tag{10}$$

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 (5) and (7)-(10) hold.

4 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 Section 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.

4.1 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 administrative regions at the county level with the aim of creating self-contained labor markets. The boundaries of local labor markets are defined such that commuting within labor market regions is relatively large compared to commuting between regions. 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 Section 2.1. Based on the results presented in Section 2.3, 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).[5] I aggregate wages to the labor market level by running the following regression for every worker group k separately:

$$\ln w_n^{raw} = \alpha_k + \beta_k X_n + d_{ik} + \epsilon_n \tag{11}$$

where X_n is a set of observable worker characteristics, d_{ik} is a group-region dummy, and ϵ_n is an error term.[6] Given the mincerian regressions, I rescale average wages according to

$$w_{ik} = \exp\left(\alpha_k + \beta_k \frac{1}{L_k} \sum_{n \in k} X_n + d_{ik}\right) \tag{12}$$

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[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.

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.

4.2 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 Figure 1. An overview of the calibrated parameters is given in Table 2.

<div align="center">

Table 2: 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

</div>

Note: The housing expenditure share is taken from official data for Germany (Statistisches Bundesamt, 2020b). The labor supply elasticities are based on own estimation presented in Section 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 (**??**) to

solve for group- and region-specific productivity fundamentals

$$A_{ik} = w_{ik}\frac{1+\eta_k}{\eta_k}. \tag{13}$$

Reformulating equation (10) gives an expression for housing fundamentals

$$H_i = (1-\alpha)\frac{\sum_k L_{ik}w_{ik}}{p_i}. \tag{14}$$

Fixed cost F can be calculated from equation (9). Summing over i and reformulating yields

$$F = \frac{\sum_i \sum_k A_{ik}L_{ik} - \sum_i \sum_k A_{ik}L_{ik}\frac{\eta_k}{1+\eta_k}}{\sum_i M_i}. \tag{15}$$

Finally, I solve the mobility constraint in equation (5) numerically for the amenity fundamentals E_{ik}

$$L_{ik} = M_i\frac{\left(\frac{w_{ik}}{p_i^{1-\alpha}}E_{ik}\right)^{\eta_k}}{\sum_{f'}\left(\frac{w_{i(f')k}}{p_{i(f')}^{1-\alpha}}E_{i(f')k}\right)^{\eta_k}}L_k \tag{16}$$

where I calculate M_i from equation (9)

$$M_i = \frac{1}{F}\sum_k L_{ik}A_{ik} - \frac{1}{F}\sum_k \frac{\eta_k}{1+\eta_k}L_{ik}A_{ik}. \tag{17}$$

5 Model fit and counterfactuals

5.1 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). The predicted number of firms and the actual number of establishments (both in logs) are strongly correlated with a correlation coefficient of 0.97.

5.2 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 labor supply elasticity while leaving all

Figure 3: Predicted number of firms
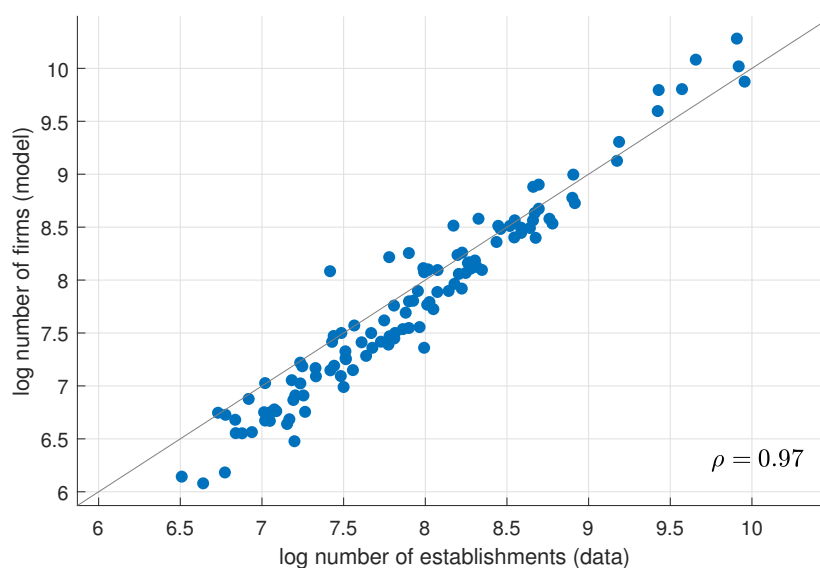
Note: The plot shows the log number of firms as predicted from the model against the log number of establishments observed in the data. Every dot represents one labor market region as defined by Kosfeld and Werner (2012).

fundamentals and remaining parameters unchanged. Figure 4 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 5. 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 5 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 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

Figure 4: The markdown distribution

Slope(SE): 0.405(0.05); 0(0)
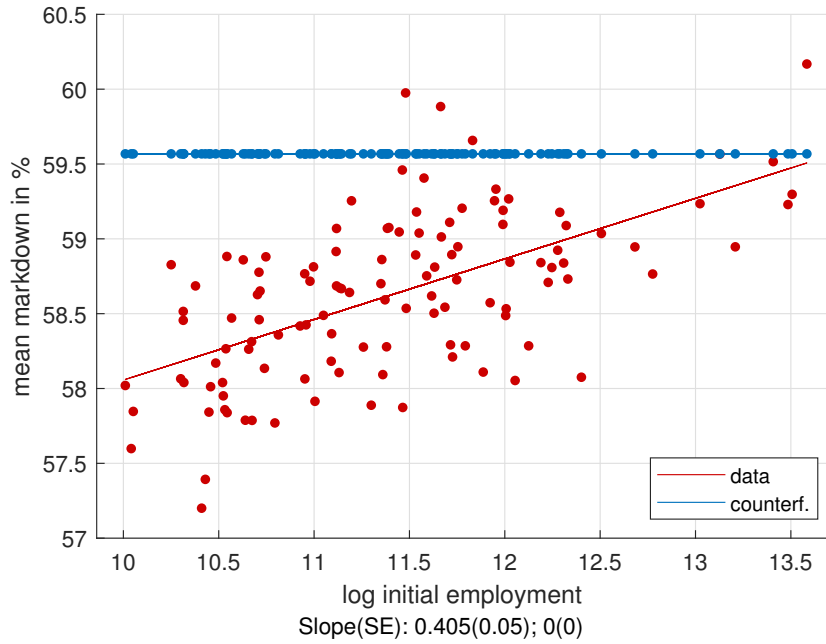
Note: The plot shows markdowns in a counterfactual in which all workers have the mean labor supply elasticity. Markdown is the ratio of wage to the marginal revenue product of labor. Every dot represents one labor market region as defined by Kosfeld and Werner (2012).

Figure 5: Wages and agglomeration with uniform markdowns

Slope(SE): 0.12(0.017); 0.108(0.016)

Slope(SE): -2.758(0.472)
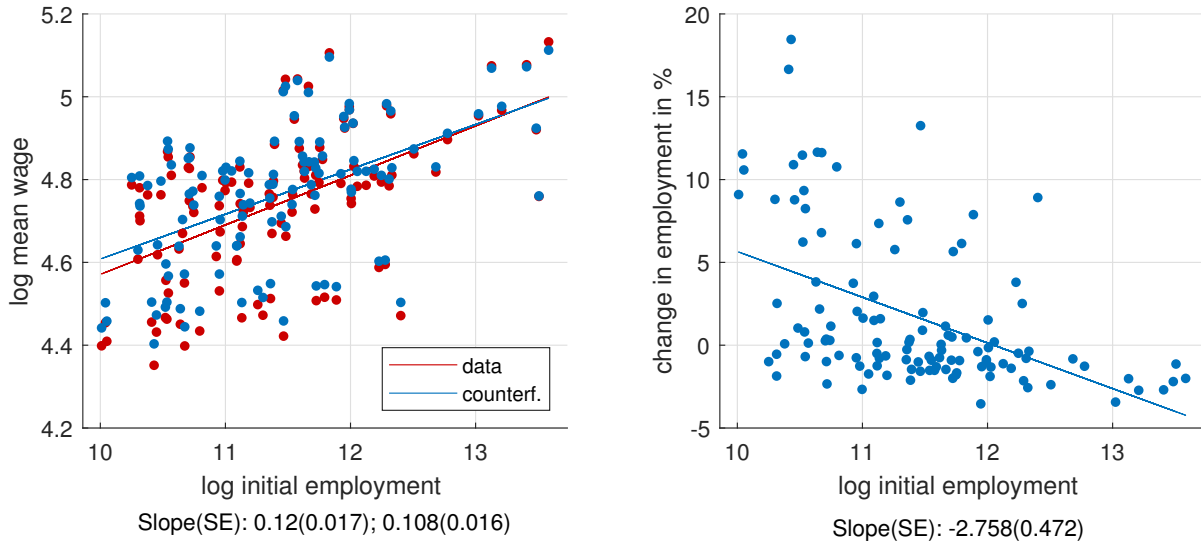
Note: The plot shows average wages (on the left) and changes in employment (on the right) in a counterfactual in which all workers have the mean labor supply elasticity. Every dot represents one labor market region as defined by Kosfeld and Werner (2012).

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, while the first two rows show the results presented in Figure 4 and Figure 5. 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.

6 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 population 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 6 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

Table 3: 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 employ-ment 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.

why workers receive a larger share of their marginal revenue product as reflected in 0.4 percent-age 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 7 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 6). The decrease in population is larger in rural areas (see the right plot of Figure 7) since the share of retiring workers is larger in these areas.

Figure 6: Markdowns after baby boomers retire

Slope(SE): 0.405(0.05); 0.392(0.047)
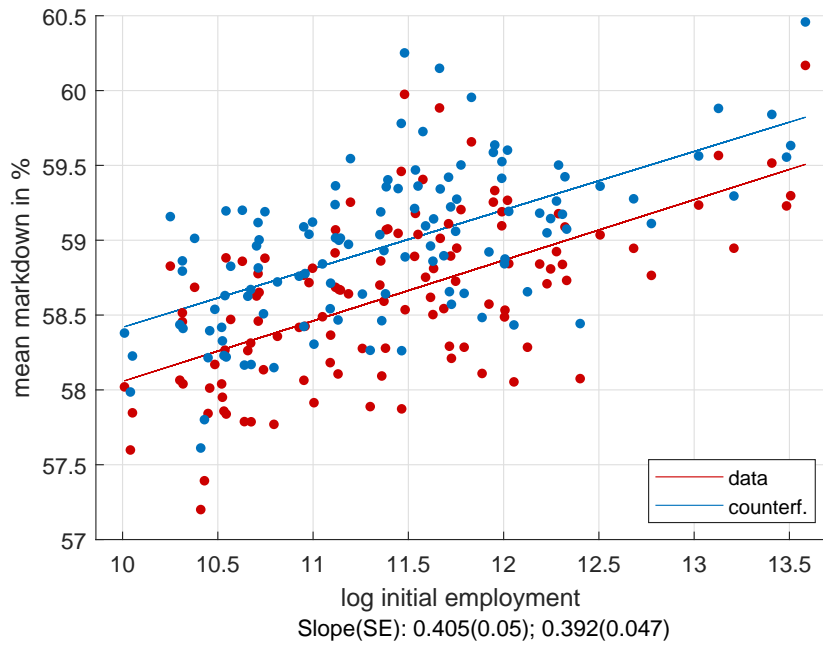
Note: The plot shows the markdown distribution in the counterfactual of retiring baby boomers. Markdown is the ratio of wage to the marginal revenue product of labor. Every dot represents one labor market region as defined by Kosfeld and Werner (2012).

Figure 7: Wages and agglomeration after baby boomers retire

Slope(SE): 0.12(0.017); 0.119(0.017)   Slope(SE): 0.441(0.12)
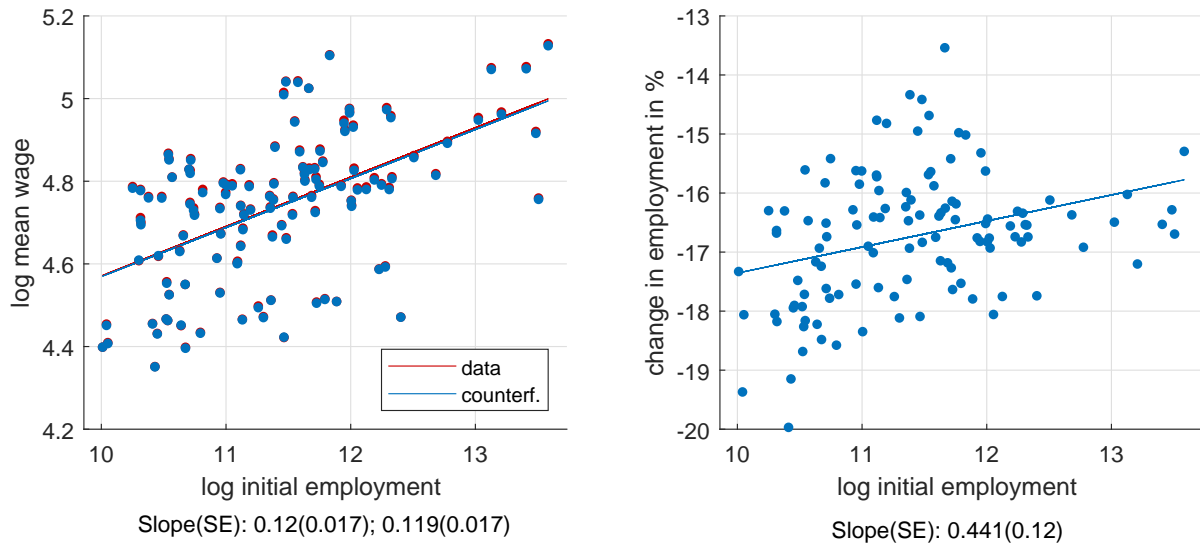
Note: The plot shows wages and agglomeration in the counterfactual of retiring baby boomers. Every dot represents one labor market region as defined by Kosfeld and Werner (2012).

7 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 differences in labor market power across worker groups and their effects on regional inequality. Using administrative data for Germany, I find that firms have significantly more wage-setting power over older and lower skilled workers. 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? To answer this question, one needs to take a stand 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. Suppose, however, that low labor mobility is the result of switching costs or non-pecuniary amenities. Then, setting incentives for workers to switch employers might not be optimal from a social planner perspective. The policy implications might however be different if labor market power results from information frictions (as in Jäger et al., forthcoming).

References

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**, "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.

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," 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," 2021.

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

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

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.

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.

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.

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

Engbom, Niklas, "Firm and Worker Dynamics in an Aging Labor Market," Technical Report, Federal Reserve Bank of Minneapolis 2019.

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, "Demographic origins of the startup deficit," *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.

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.

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

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.

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," 2019.

_ , "Bevölkerungsvorausberechnung," 2020.

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

_ , "Erwerbspersonenvorausberechnung," 2020.

A Appendix

A.1 Descriptives

Table A1: Summary statistics – individual-level data

	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 in Section 2 that is based on quarterly individual-level data from 1994 to 2014. Wages are gross daily wages.

Table A2: Sample statistics – data on the labor market level

	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 A1: Demographics across districts
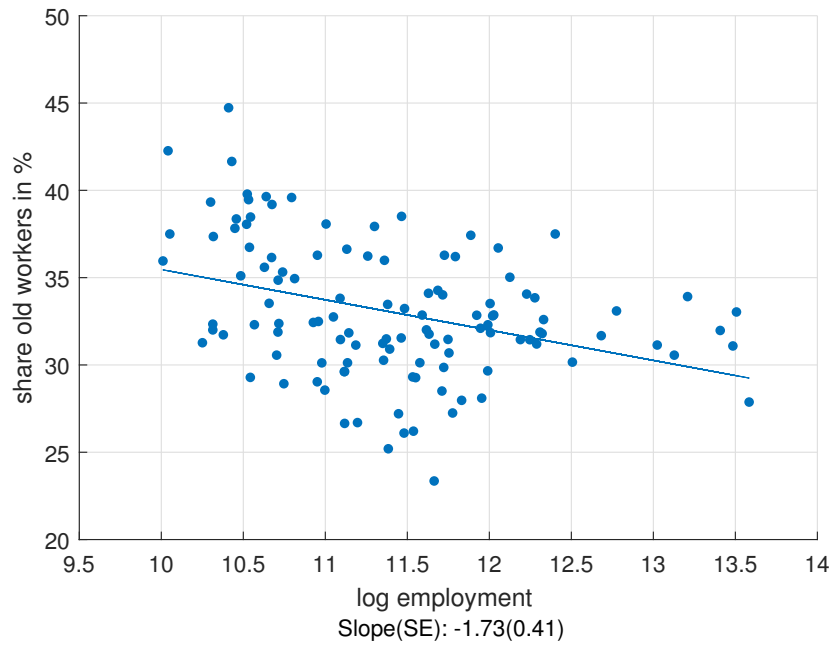
Note: The plot shows the share of workers in the age group 50 to 64 (relative to workers aged 20 to 64). Every dot represents one labor market region as defined by Kosfeld and Werner (2012).

A.2 Labor supply elasticity estimates

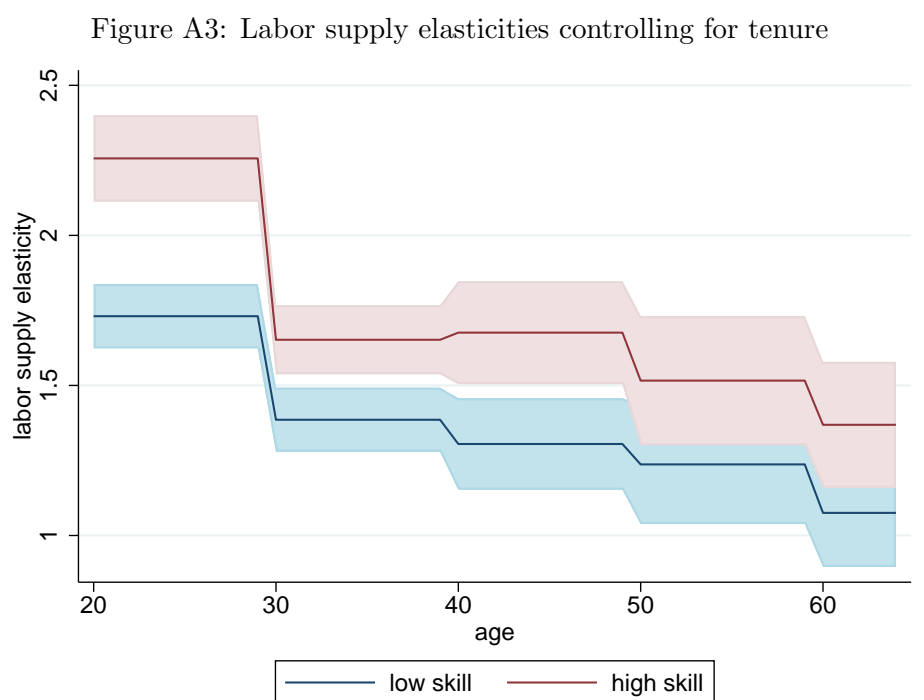Figure A2: Labor supply elasticity estimates across districts
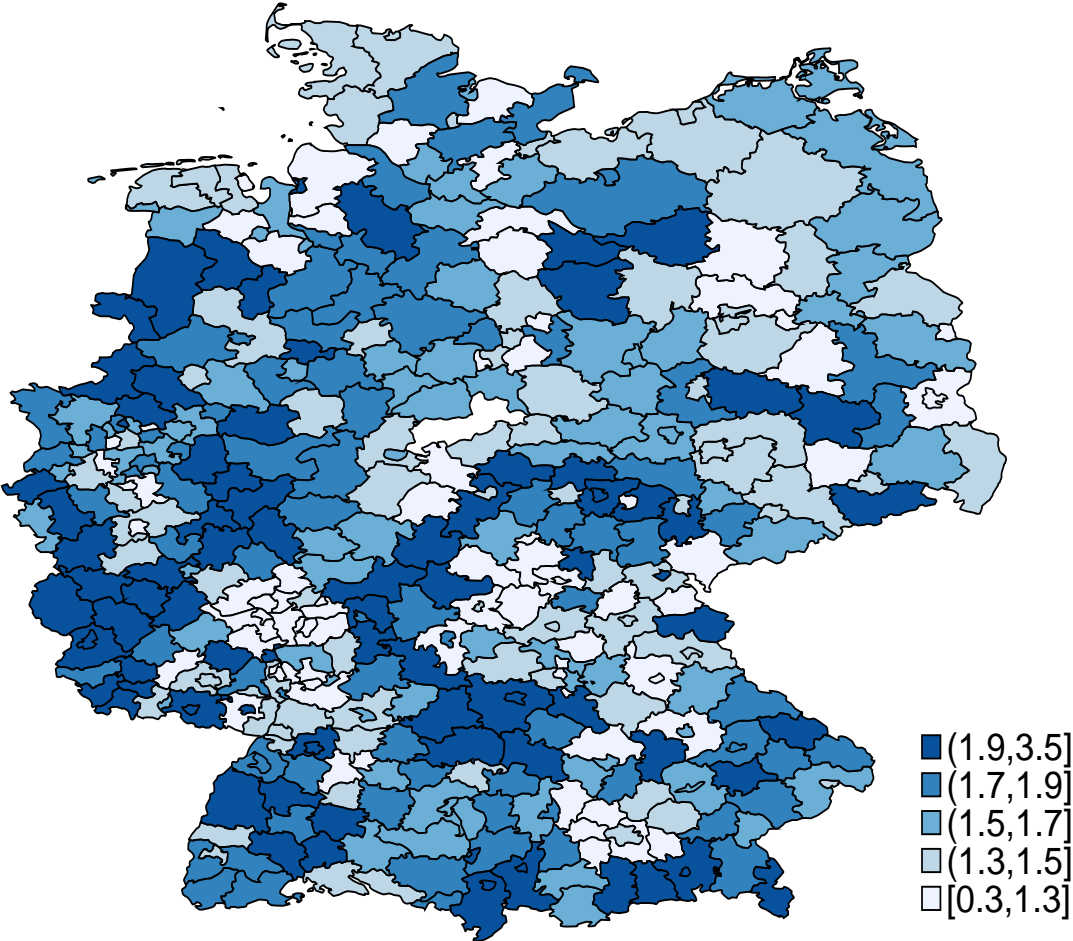
Note: The plot shows the variation in the estimated labor supply elasticities across districts. The estimates are based on the regression results from estimating the model in equation (1). The regression coefficients are transformed into estimates of the labor supply elasticity by dividing by the group-specific mean of the outcome and multiplying with -2.

A.3 Robustness checks

Controlling for tenure

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 A3 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.

Figure A3: 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.

Estimating skill-specific age coefficients

To get a better understanding of what drives differences in labor supply elasticities across age groups, I As a robustness test, I estimate the model in equation (1) with one skill-coefficient for every age group. The results in Figure A4 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.
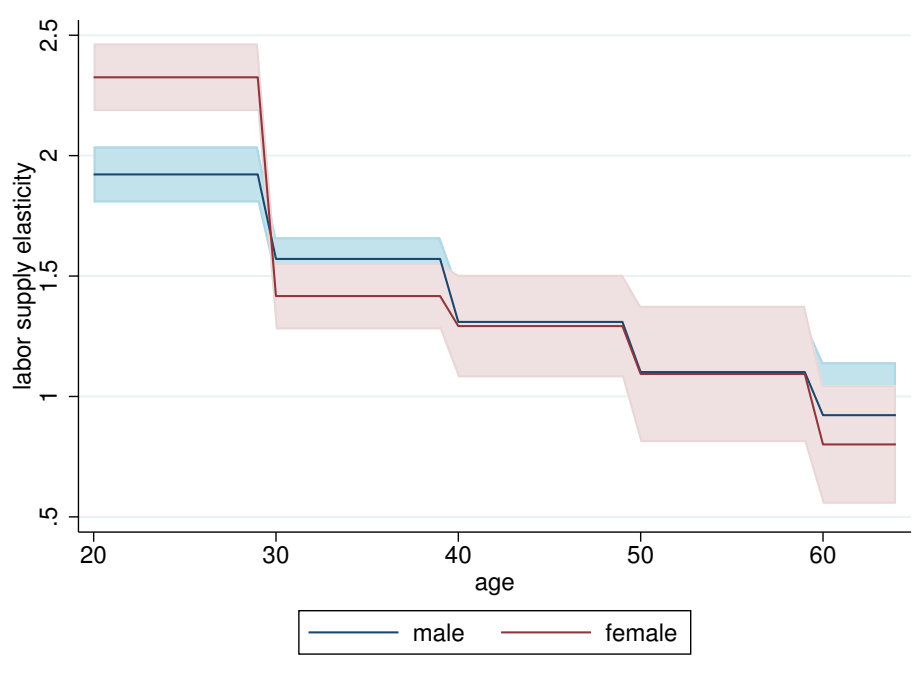
Figure A4: Labor supply elasticities by gender
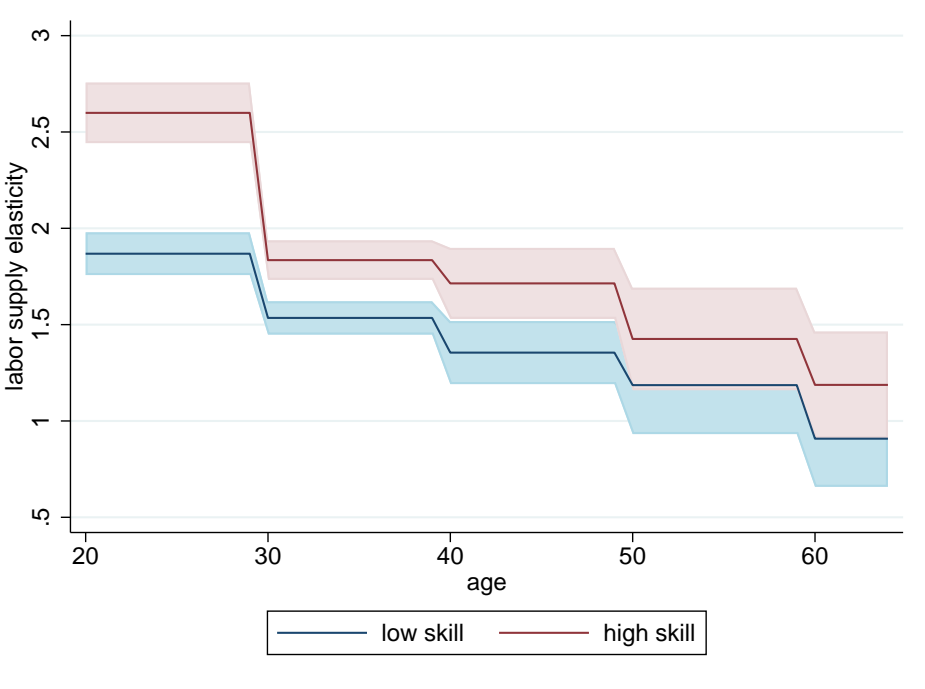
Note: The plot shows the regression results when estimating the model in equation (1) with a separate coefficient for every group defined by the interaction of skill and age. The coefficients are transformed into estimates of the labor supply elasticity by dividing by the group-specific mean of the outcome and multiplying with -2. The shaded areas represent 95% confidence intervals.

Estimating gender-specific age coefficients

In Section 2.3, 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 on the labor supply elasticity differs by gender. To investigate the problem, I estimate the model in equation (1) with gender-specific effects of age and skill on the labor supply elasticity. Figure A5 shows that there are no significant differences between labor supply elasticities of male and female workers from age 30 to 64.

Figure A5: Labor supply elasticities by gender

Note: The plot shows the regression results when estimating the model in equation (1) 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.

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