Supplemental Appendix

Demographics, Labor Market Power and the Spatial Equilibrium

By Nina Furbach

A. Summary Statistics

Table A.1—Summary statistics – data at the individual level

	mean	p10	p50	p90	sd
separation	0.103	0	0	1	0.304
wage	108.037	47.797	91.164	178.303	75.197
age	38.716	25	38	54	10.586
college degree	0.158	0	0	1	0.365
N	19 710 396				

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

Table A.2—Summary statistics – data at the labor market level

	mean	sd	min	max
Low skilled				
age 20-49				
wage	96.99	10.99	76.27	118.83
employment (in thd)	68.75	67.85	11.85	363.30
age 50-64				
wage	103.21	12.78	79.92	124.92
employment (in thd)	33.30	32.74	6.85	173.85
High skilled				
age 20-49				
wage	175.56	23.21	121.04	235.57
employment (in thd)	19.99	33.83	1.30	230.60
age 50-64				
wage	206.59	33.84	129.30	268.70
employment (in thd)	8.64	13.08	1.10	75.55
House purchase price	1.06	0.45	0.35	2.96

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.

B. Visualization of the instrumental variable regression

This Section provides graphical evidence that illustrates the regional variation in the key relationships used to estimate labor supply elasticities to the firm. The left panel of Figure B.1 visualizes the first stage of the instrumental variable estimation. It shows the average quarter-on-quarter growth rate of individual-level wages against the growth rate of predicted wages. Predicted wages are obtained from the first stage of the instrumental variable estimation, where individual-level wages are regressed on the average national wage of individuals in the same 3-digit occupation, excluding from the calculation workers in the same region. Each point represents one labor market region as defined in Kosfeld and Werner (2012). Both variables averaged over the sample period. The figure indicates that the variation in the occupational wage measure is strongly correlated with individual wage growth, as required for a relevant instrument.[1]

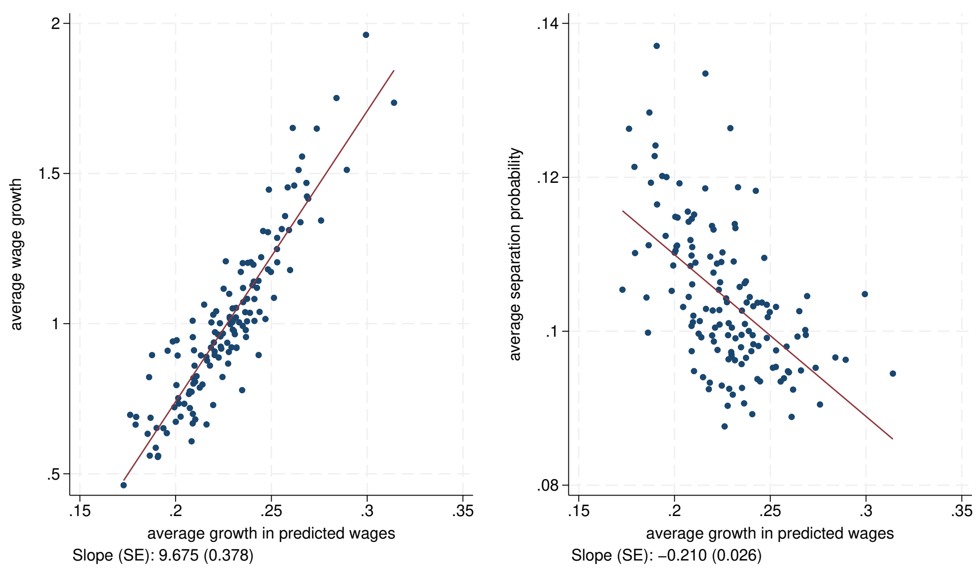

Figure B.1. First- and Second-Stage Regression

Note: The left panel shows the average quarter-on-quarter growth rate of individual-level wages against the growth rate of predicted wages. The right panel depicts the average of a separation indicator that equals one if an individual leaves her employer in a given quarter. Every dot represents one labor market region as defined in Kosfeld and Werner (2012).

[1]Note that the average growth rate of predicted individual-level wages is lower than that of actual wages, since predicted wages have a smaller variance than observed wages.

In addition, I present a visualization of the second-stage regression. The right panel of Figure B.1 plots regional averages of the outcome variable against the average growth in wages predicted from the first-stage regression. The outcome variable is a separation indicator that equals one if an individual leaves her employer in a given quarter. The chart shows a significant negative relationship, in line with the reduced-form estimates presented in the paper: in regions in which individual-level wages have grown more strongly on average over the sample period, individuals have less often left their employer. This negative relationship suggests an upward-sloping labor supply curve.

C. Robustness

Assuming alternative functional forms

I start with testing the assumption that the effect of age on workers' labor supply elasticity can be approximated by splitting workers into five different age groups. Figure C.1 shows labor supply elasticity estimates from assuming alternative functional forms in age. The quadratic and the cubic specification reveal that labor supply elasticities decrease strongly in the beginning of the work life cycle, but start to level off around the age of 40. The flatter labor supply elasticities at older ages are captured well by the five age brackets, while the baseline specification seems to provide a lower bound of the decline in labor supply elasticities between age 20 to 40.

Controlling for compositional differences across worker groups

The model specified in equation (1) might suffer from endogeneity due to compositional differences across age groups. First, the female labor force participation rate might be lower for older age groups, while several studies have shown that females have a lower labor supply elasticity than males (Barth and Dale-Olsen, 2009; Hirsch, Schank and Schnabel, 2010). Older age groups might show a greater sensitivity to wage differences because of their higher shares of males relative to younger age groups. Estimating equation (1) without controlling for gender-specific labor supply elasticities might thus yield coefficients that underestimate the causal effect of age on labor supply elasticities due to omitted variable bias.

Secondly, older workers tend to sort into rural areas relative to younger workers, while at the same time there is evidence that labor market power is larger in rural areas (see Bamford, 2021 and Hirsch et al., 2022). The coefficients from estimating equation (1) might thus attribute lower labor supply elasticities of older workers to their age which might be causally driven by their geographic sorting behavior. I therefore test the robustness of the results to the inclusion of region-specific labor supply elasticities. By comparing younger with older workers in the same region, this robustness test also ensures that the results are not driven by differential changes in housing costs across regions.

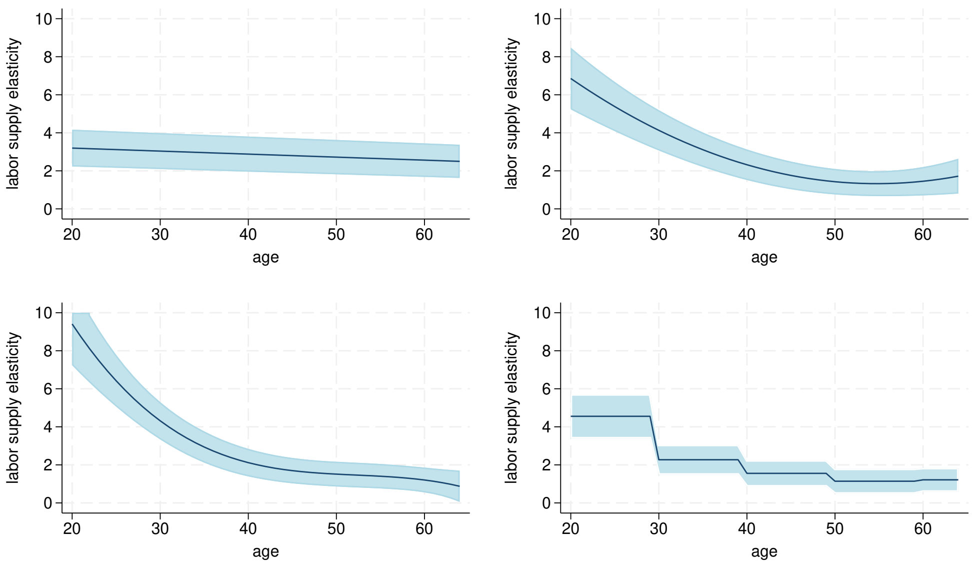

Figure C.1. Labor supply elasticity estimates from different specifications

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.

Last, there might be sorting of age groups across sectors while labor supply elasticities might not be constant across industries. Consider for example industries that have shrunk over time. The workforce in these industries is likely older than in other sectors, since younger individuals might be reluctant to decide to work in these sectors. If skills are not easily transferable to other industries, labor market power will be higher. Thus, not controlling for sector-specific labor supply elasticities would, for the given example, lead to an overestimation of the effect of age on the labor market power of firms.

To deal with endogeneity issues steming fom compositional differences across age groups, I include an interaction term of log wages 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 the sensitivity of older workers to differences in wages with the sensitivity of younger workers of the same gender within the same sector and region.[2]

The coefficients presented in specifications (2) to (4) of Table C.1 reveal that the

[2] I use 15 sectors as defined by Dauth and Eppelsheimer (2020) and 141 labor market regions as defined by Kosfeld and Werner (2012).

results are not driven by compositional differences across age groups. Specification (1) shows the baseline results. While the magnitude of the coefficients differs across specifications, the pattern of a weaker separation response to wages for older workers remains robust across specifications.

Table C.1—Sensitivity of Worker Turnover – Robustness

	(1)	(2)	(3)	(4)	(5)
log(wage) ×					
age 20-29	-0.233	-0.265	-0.233	-0.198	-0.237
	(0.0304)	(0.0319)	(0.0335)	(0.0257)	(0.0291)
age 30-39	-0.116	-0.144	-0.113	-0.0854	-0.129
	(0.0206)	(0.0220)	(0.0278)	(0.0178)	(0.0204)
age 40-49	-0.0787	-0.104	-0.0768	-0.0497	-0.104
	(0.0181)	(0.0192)	(0.0267)	(0.0158)	(0.0195)
age 50-59	-0.0576	-0.0818	-0.0569	-0.0291	-0.0982
	(0.0172)	(0.0182)	(0.0265)	(0.0153)	(0.0200)
age 60-64	-0.0613	-0.0854	-0.0598	-0.0334	-0.117
	(0.0164)	(0.0175)	(0.0259)	(0.0146)	(0.0206)
college degree	-0.00657	-0.00651	-0.00652	-0.00695	-0.00560
	(0.00141)	(0.00138)	(0.00144)	(0.00135)	(0.00132)
female		0.0887			
		(0.0154)			
tenure					0.00173
					(0.000653)
tenure^2					0.000119
					(0.00000492)
worker FE	yes	yes	yes	yes	yes
sector FE				yes	
sectoral elast.				yes	
region FE			yes		
regional elast.			yes		
Kleibergen-Paap F-stat	71	61	4	34	54
N	19710046	19710046	15838785	19708820	19710046

Note: Standard errors in parentheses, clustered by occupation*worker group. The dependent variable is a separation indicator. Wages are instrumented with the average wage in the same occupation, excluding the own labor market region as defined by Kosfeld and Werner (2012). Specification (3) excludes all labor market regions with less than 100 individuals for each worker group. Male workers without a college degree are the reference group in specification (2), workers without a college degree are the reference group in all other specifications.

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 the last column of Table C.1 show a smaller variation in the labor supply elasticity than the baseline results. The pattern of a decreasing elasticity over the life cycle remains however unchanged.

Estimating skill-specific age coefficients
As a further robustness check, I estimate the model in equation (1) with one skill-coefficient for every age group. The results in Figure C.2 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.

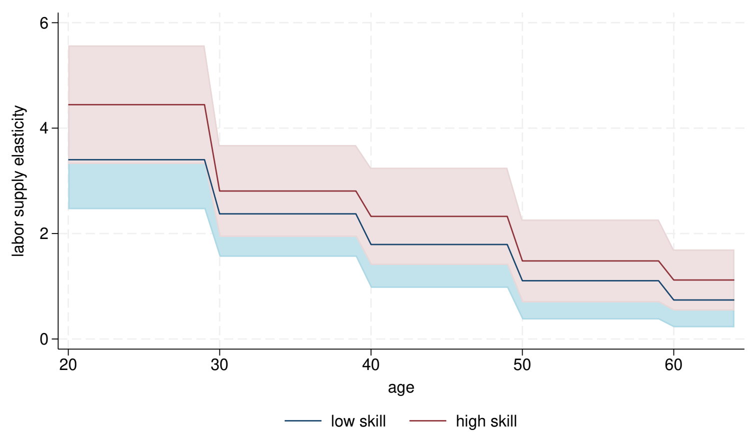

FIGURE C.2. LABOR SUPPLY ELASTICITIES WITH SKILL-SPECIFIC AGE COEFFICIENTS

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.

Labor supply elasticities and concentration
In Section I.D, I have shown the baseline results on labor supply elasticities across worker groups to be robust to controlling for the effect of the labor share on the labor supply elasticity. While this finding suggests the results not to be driven by the strategic interaction of firms, I investigate in this section more broadly the role of outside options. To do so, I estimate the baseline regression

specified in equation (1) controlling for the degree of concentration in the labor market, as measured by the HHI, and its interaction with the log wage. Figure C.3 shows that the labor supply elasticity decreases with the degree of concentration in the labor market, although the decline is not statistically significant (left panel). Differences in labor supply elasticities across age groups do not seem to be driven by the availability of outside options (right panel). I also estimate regressions where I interact log wages, the HHI and dummy variables for different age groups. I find that the effect of concentration on the labor supply elasticity does not differ across age groups.

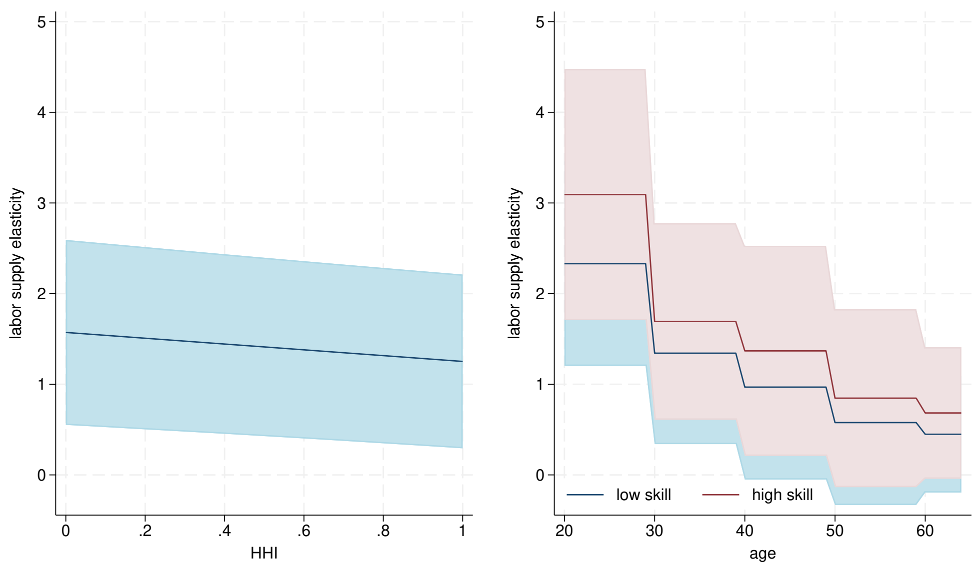

Figure C.3. Labor supply elasticities and labor market concentration

Note: The left panel shows estimates of the labor supply elasticity depending on the degree of concentration in the labor market, which is defined by the interaction of the labor market region (see Kosfeld and Werner, 2012) and the 5-digit industry. The right panel shows estimates of the labor supply elasticities for different worker groups when controlling for concentration. The shaded areas represent 95% confidence intervals.

REFERENCES

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

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

Dauth, Wolfgang, and Johann Eppelsheimer. 2020. "Preparing the sample of integrated labour market biographies (SIAB) for scientific analysis: a guide." *Journal for Labour Market Research*, 54(10): 1–14.

Hirsch, Boris, Elke J Jahn, Alan Manning, and Michael Oberfichtner. 2022. "The urban wage premium in imperfect labor markets." *Journal of Human Resources*, 57: 111–136.

Hirsch, Boris, Thorsten Schank, and Claus Schnabel. 2010. "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*, 28(2): 291–330.

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

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