Labour Market Concentration and Worker Mobility: Evidence from Online Vacancies

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1 Introduction

This article builds on an oligopsony model by Boal & Ransom (1997), which predicts that wages decrease as labour market concentration increases. With an upward-sloping labour supply, the decrease in wages reduces employment and labour market concentration causes deadweight loss. We estimate labour market concentration with online vacancy data from Germany and investigate the impact of local labour market concentration on wages.

The wage effects of labour market concentration have been studied earlier, but this is the first paper to also study the heterogenous effect of labour market concentration between remote and non-remote workers. In theory, remote workers should not be affected by local labour market concentration because they are mobile and can move to other labour markets. Our objective is to test whether increasing remote work or worker mobility could be a successful policy response for labour market concentration.

Most studies calculate Herfindahl-Hirschman indexes (HHI) for labour market concentration based on the employment share of each firm in geographic-occupational labour markets (e.g. Abel, et al., 2018; Bassanini et al., 2022; Benmelech et al., 2022; Rinz, 2022). We use vacancy shares instead, because we consider vacancies to be a better measure of workers' outside options. When negotiating for wages, the bargaining power of workers is increased only if there are vacancies available as alternatives and employment shares may underestimate concentration if jobs are not vacated frequently. Vacancy-based analyses with US data find large negative wage effects from labour market concentration (Azar et al., 2020; Azar et al., 2022) and this paper investigates whether a similar effect exists in a European country with different labour market institutions than US.

2 Estimating Labour Market Concentration

2.1 Data

Our near-universe dataset from Eurostat Web Intelligence Hub (Appendix-1) covers all vacancies posted online in Germany during 2020. It includes approximately 7.3 million postings with information on education and experience requirements and over 50 other variables. Posted wage is available for 12.5% of the postings and we use wage data for full-time employees with unlimited contracts because we have data only on annual wages.

2.2 Herfindahl-Hirschman Index (HHI)

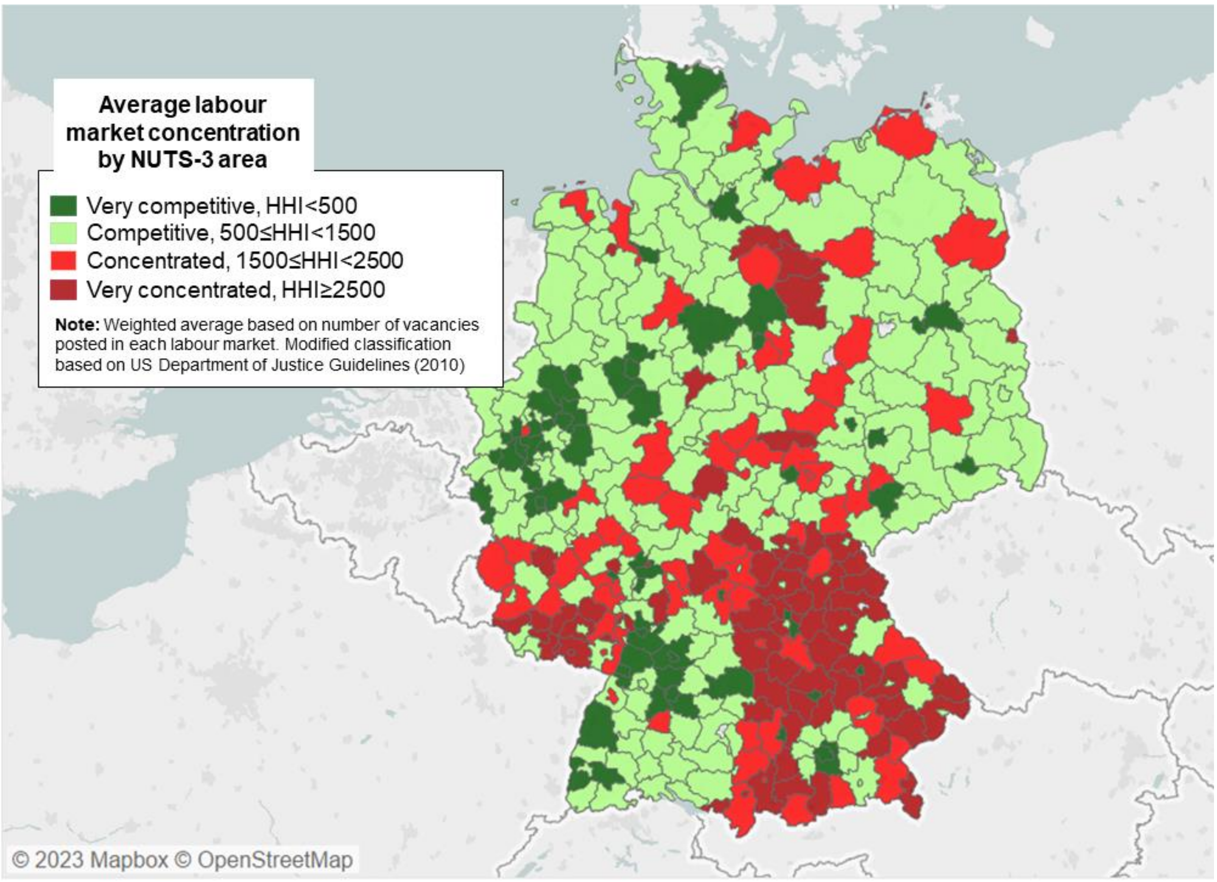
We estimate labour market concentration with HHI, calculated based on the number of vacancies posted by firms in geographic-occupational labour markets.

$$HHI_{m,q} = \sum_{j=1}^{J} s_{j,m,q}^{2}.$$

The variable s is the share of vacancies expressed as a number between 0 to 100 that firm j has in market m during a quarter q. A single labour market is defined as all workers within a 3-digit ESCO occupation classification inside a NUTS-3 region (ESCO, 2022; Eurostat, 2023).

For 37.6% of vacancies, the dataset does not include the name of the posting company. We assume that vacancies with a missing company name are posted by different individual firms, and thus our estimates provide a lower-bound for labour market concentration. Azar et al. (2022) use the same assumption with online data from the US.

The median vacancy is posted in a competitive labour market ($HHI \approx 168$) but especially labour markets in rural areas can be concentrated.



3 Results

3.1 Wage Effects

In our main specification vector X includes all controls and β measures the elasticity of posted wages (w) with respect to HHI.

$$\log w = \alpha + \beta \times \log HHI + \gamma_i^T X$$

The relationship between labour market concentration and wages is causal only if labour supply and total market demand are held constant (Boal & Ransom, 1997). In a simplified model, total market demand depends on the value of marginal product, which is a function of labour productivity and output market price.

We first use OLS, and proxy for labour productivity with education and experience controls, while occupation and area fixed effects control for labour supply. This implies no statistically significant effect (Table-1), but there are multiple reasons to believe that this result is biased.

Firstly, there might be market-level, time-varying labour supply and demand effects. For example, the labour supply within a specific labour market might become constrained within some period, which would increase wages because the firms must compete over employees. This could lead us to falsely conclude that labour market concentration has no impact on wages, because labour supply is more likely to become constrained in concentrated labour markets within rural areas. Secondly, wages could be influenced by time-varying firm specific effects. Finally, firms may choose to post wages online only for specific types of vacancies (e.g. mainly for low-wage workers).

Thus, we instrument HHI using the leave-one-out instrument (LOO), which predicts local labour market concentration based on the likely concentration in other markets within the same occupation. Specifically, we instrument $\log HHI_{o,g,q}$ with the average of $\log\left(\frac{1}{N_{o,g',q}}\right)$ where $N_{o,g',q}$ is the number of firms who posted a vacancy in all other geographical areas g' within the same occupation o and quarter q.

The instrument is commonly used (e.g., Azar et al. 2022; Bassanini et al., 2022; Rinz, 2022) and is likely uncorrelated with the three main factors – labour productivity, product market price and labour supply – identified here as influencing wages. First-stage regression shows that the instrument is strong with a t-statistic of 76.24 (Table-2).

Based on the main IV estimate, a 1% increase in labour market concentration decreases posted wages for full-time employees by 0.098% (Table-1, column 2). This is in line with our expectation that OLS underestimates the impact of labour market concentration on wages. Moving from the median ($HHI \approx 168$) to a highly concentrated market ($HHI = 2500$) decreases wages by 23.25%.[1]

The main threat to identification is that productivity shocks to occupations could be correlated across areas. In IV specifications, we can't control for occupation fixed effects because this is the level at which our instrument is defined at (Azar et al., 2022). For example, a national level decline in the productivity of some occupation would increase concentration and decrease wages in most labour markets within that occupation. The instrument protects against spurious correlation between concentration and outcomes that is due to local changes in productivity, but not against national-level changes in productivity that influence both concentration and other labour market outcomes.

[1] Wages change by $(\ln(2500) - \ln(168)) \times (-0.098) = -0.264 \ldots$ log-points, which translates to $(e^{-0.264\cdots} - 1) \times 100\% \approx -23.25\ \%$

Table-1: Main results

VARIABLES	(1) OLS Log Wages	(2) IV Log Wages	(3) IV Log Wages
Log HHI	0.0165	-0.0981***	-0.101***
	(0.0183)	(0.0190)	(0.0190)
Remote × Log HHI			0.145***
			(0.0410)
Remote			-0.746***
			(0.187)
Fixed effects	Area & Occupation	Area	Area
Other control variables	Education, experience, quarter	Education, experience, quarter	Education, experience, quarter
Instruments	None	LOO	LOO, LOO×Remote
Observations	11,603	11,603	11,603
R-squared	0.176	0.131	0.124

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table-2: First-stage regressions

VARIABLES	(1) Log HHI	(2) Log HHI	(3) Remote × Log HHI
LOO	0.581***	0.603***	-0.0481***
	(76.24)	(78.02)	(-6.563)
Remote × LOO		0.222***	0.734***
		(12.74)	(26.81)
Remote		1.399***	11.12***
		(8.669)	(44.28)
Fixed effects	N/A	Area & Occupation	Area
Other control variables	Education, experience	Education, experience, quarter	Education, experience, quarter
Observations	11,603	11,603	11,603
R-squared	0.831	0.867	0.915

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

3.2 Wage Effects for Remote Workers

Appendix-2 lists occupations, such as developers and sales staff, in which there were likely remote work opportunities available during the pandemic year of 2020. We define a binary variable $remote$, which equals 1 if the vacancy is for any of these occupations. We add $remote$ and the interaction term $\log HHI \times remote$ to our earlier specification.

$$\log w = \alpha + \beta \times \log HHI + \mu \times \log HHI \times remote + \delta \times remote + \gamma_i^T X$$

The elasticity of wages on HHI for remote workers is $\beta + \mu$. We continue to instrument log-HHI with the leave-one-out instrument (LOO) while the interaction term is instrumented with $LOO \times Remote$. Arguments for exogeneity remain the same as earlier, and instruments are strong based on first-stage regressions (Table-2).

Workers with remote work opportunities do not face negative wage effects for local labour market concentration, and the estimated coefficient for remote workers is even positive, although moderately small in magnitude (Table-1, column 3). In this specification the wage effect for other workers is also slightly larger than estimated earlier.

3.3 Robustness Checks

Top-Coding

Wages are top-coded with a maximum annual wage of 90000€ and we estimate specifications from Table-1 also with Tobit models. The estimated coefficients are almost identical to the ones found earlier, which suggests that top-coding is unlikely to influence our results. This is expected because only 5.72% of the wage offers are above 90000€.

Table-3: Tobit estimates

VARIABLES	(1) Tobit Log Wages	(2) IV-Tobit Log Wages	(3) IV-Tobit Log Wages
Log HHI	0.0139	-0.0949***	-0.0978***
	(0.0182)	(0.0182)	(0.0182)
Remote × Log HHI			0.146***
			(0.0399)
Remote			-0.747***
			(0.182)
Fixed effects	Area & Occupation	Area	Area
Other control variables	Education, experience, quarter	Education, experience, quarter	Education, experience, quarter
Instruments	None	LOO	LOO, LOO×Remote
Observations	11,603	11,603	11,603

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Spillover Effects

We use relatively small NUTS-3 areas as the boundaries for our labour markets because studies show that the attractiveness of jobs to applicants sharply declines with distance (Manning & Petrongolo, 2017; Marinescu & Rathelot, 2018). However, with the small NUTS-3 areas workers might be able to switch away from a concentrated market to a less concentrated one, which reduces labour supply in the concentrated market and increases supply in the less concentrated one. This causes an increase in wages in the concentrated market and a decrease in wages in the other one, which might lead us to underestimate the impact of labour market concentration.

Because of these potential spillovers, we conduct alternative specifications in which we define single labour markets based on the larger NUTS-1 and NUTS-2 areas. The main results remain the same, although the estimated wage effect from local labour market concentration is slightly larger in magnitude.

Table-4: Alternative definitions for local labour markets

VARIABLES	(1) IV Log Wages	(2) IV Log Wages	(3) IV Log Wages	(4) IV Log Wages
Log HHI	-0.146***	-0.121***	-0.159***	-0.131***
	(0.0212)	(0.0195)	(0.0217)	(0.0200)
Remote × Log HHI			0.205***	0.173***
			(0.0466)	(0.0406)
Remote			-0.757***	-0.731***
			(0.142)	(0.145)
Fixed effects	Area	Area	Area	Area
Other control variables	Education, experience, quarter	Education, experience, quarter	Education, experience, quarter	Education, experience, quarter
Instruments	LOO	LOO	LOO, LOO×Remote	LOO, LOO×Remote
Definition of a single labour market	3-digit occupations within NUTS-1 areas	3-digit occupations within NUTS-2 areas	3-digit occupations within NUTS-1 areas	3-digit occupations within NUTS-2 areas
Observations	11,603	11,603	11,603	11,603
R-squared	0.033	0.054	0.050	0.124

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4 Conclusion

Based on IV results, a 1% increase in labour market concentration decreases posted wages for full-time employees by 0.098% in Germany. The median labour market in Germany is competitive, but labour market concentration can cause significant downward pressure on wages in rural areas, potentially causing a wage gap between rural and urban workers and thus contributing to wage inequality.

Workers who can work remotely do not face negative wage effects from labour market concentration. This suggests that supporting labour mobility and remote work can potentially mitigate the negative effects of labour market concentration. Example policies include worker mobility schemes (e.g. EURES, 2023) or legislation which gives employees the right to request remote work (Gov.ie, 2022). As a large employer in many countries, the public sector can also ensure as many remote work opportunities as possible.

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Appendix-1: Note on Data Processing

The Eurostat Web Intelligence Data Hub captures online vacancies. The algorithm used to capture online vacancies also captures duplicates because the same posting can appear in multiple websites. All duplicate postings are given the same id. When downloading the data, we used a Python code which removed all duplicates leaving us with a dataset of approximately 7.3 million unique postings. A limitation with this dataset is that not all variables are observed for the whole dataset either because the algorithm has not captured full information from the posting or because the firm has posted a vacancy with incomplete information. We deal with missing information in each section separately. Access to the database can be requested from Eurostat.

Read more: https://cros-legacy.ec.europa.eu/content/trusted-smart-statistics-%E2%80%93-web-intelligence-hub_en

Appendix-2: List of Remote Work Occupations

Occupation code	**Occupation description**
OC251	Software and applications developers and analysts
OC331	Financial and mathematical associate professionals
OC333	Business services agents
OC241	Finance professionals
OC252	Database and network professionals
OC412	Secretaries (general)
OC134	Professional services managers
OC261	Legal professionals
OC335	Regulatory government associate professionals
OC212	Mathematicians, actuaries and statisticians
OC111	Legislators and senior officials
OC122	Sales, marketing, and development managers
OC243	Sales, marketing, and public relations professionals
OC242	Administration professionals
OC431	Numerical clerks
OC524	Other sales workers
OC334	Administrative and specialised secretaries
OC351	Information and communications technology operations and user support technicians
OC133	Information and communications technology service managers
OC264	Authors, journalists, and linguists
OC413	Keyboard operators
OC231	University and higher education teachers
OC352	Telecommunications and broadcasting technicians