

Monopsony: Wages, wage bargaining and job requirements *

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Abstract

Using linked vacancy-employer-employee data from Austria, we investigate how monopsony power affects firms' posting behavior and wage negotiations. Consistent with theoretical predictions, we find that firms with greater monopsony power post lower wages and offer fewer non-wage amenities, suggesting that wages and non-wage benefits are complementary. However, we find no evidence that monopsonistic firms demand higher levels of skill or education. Instead, our results indicate that they require more basic skills, particularly those related to routine tasks. On the workers' side, we find that employees hired in monopsonistic labor markets face significantly lower wages, both initially and in the long run. These lower wages are driven by both lower posted wages and reduced bargaining power, as well as reduced opportunities to climb the wage ladder later.

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1 Introduction

Monopsony in its old form of a company town starting with [Robinson \(1933\)](#) or in its new dynamic form ([Manning, 2021](#)) is a thriving concept capable of explaining the power of the employer to set the wages and work environment ([Card, 2022](#)). Several articles show that monopsony leads to lower wages for workers ([Rinz, 2022](#); [Marinescu et al., 2021](#); [Benmelech et al., 2022](#); [Bassanini et al., 2024](#); [Hirsch et al., 2018, 2022](#); [Qiu and Sojourner, 2023](#)). At the same time, studies of job postings show the ability of firms in more concentrated markets to request better formal or informal qualifications or skills from applicants ([Hershbein et al., 2018](#); [Modestino et al., 2020](#)). Despite compelling evidence that monopsony power harms workers, the precise mechanisms remain unclear. Firms may leverage their monopsony power when advertising job openings, potentially offering lower wages. Alternatively, the full effects of monopsony power may only materialize during wage negotiations between the firm and workers. Understanding which of these two channels is primarily responsible for wage losses is crucial for policy makers and for shaping the organization of the labor market. For instance, if lower wages in monopsonistic markets are mainly driven during firm-worker negotiations, policymakers could establish accessible resources, such as wage information hubs, to help workers understand negotiation strategies and industry pay standards.¹

Using linked administrative vacancy-employer-employee data for Austria, we present evidence that lower wages in monopsonistic labor markets are driven by both lower posted wages and reduced bargaining power. Approximately half of the wage loss results from firms offering lower wages in concentrated labor markets, while the other half comes from workers facing worse bargaining conditions after applying. We also document that these effects are highly persistent: workers who initially started a new job in a highly concentrated-market firm continue to earn significantly lower wages even after ten years.

We complement our wage analysis by examining non-wage amenities offered by firms. In monopsonistic labor markets, firms are less likely to offer non-wage amenities. This suggests that workers view non-wage amenities as complements to wages, but also that such amenities are under-provided in monopsonistic markets ([Dube et al., 2022](#)). However, we do not find evidence that monopsonistic firms require higher skill levels. Instead, we find that these firms demand more basic skills related to routine and lower-productivity work.²

We contribute to the existing literature in three important ways. First, there is an increasing number of research showing that concentration negatively affects the wages of new hires (e.g. [Rinz \(2022\)](#), [Qiu and Sojourner \(2023\)](#), [Benmelech et al. \(2022\)](#), [Bassanini et al. \(2021\)](#), [Lipsius \(2018\)](#), and many more). A paper closely related to our research is [Marinescu et al. \(2021\)](#), who contribute to this strand of literature by examining how the market power of employers affects wages and employment in France. Other studies look at the explicit effect of mergers on outcomes of labor market concentration (e.g. [Arnold \(2019\)](#), [Kim et al. \(2021\)](#) or [Prager and Schmitt \(2021\)](#)). Our contribution to this literature follows closely these methodological ideas;

¹[Frimmel et al. \(2023\)](#) finds that providing wage information in job postings can help reduce the gender wage gap, citing a reform in Austria that required companies to include wage details in job ads.

²These results complement [Bachmann et al. \(2023\)](#), who show that monopsony power leads to smaller and less productive firms.

but we can also offer more comprehensive results by looking at wages, non-wage amenities and job requirements at the same time. Moreover, we analyze whether these wage losses are due to lower bargaining power of workers or whether firms in more concentrated markets offered such lower wages in the first place. Some studies (Prager and Schmitt (2021), Schubert et al. (2023), Abel and Sunde (2018) or Izumi et al. (2023)) argue that monopsony effects should be smaller in situations with strong unions, but larger for less mobile workers; we offer evidence for Austria with a strongly falling union share (Anton et al., 2022) and relatively immobile workers.³

Other studies use quit rates as a measure of labor market power and compare quit elasticities - a measure of how much more likely a worker is to quit a job in response to a small wage change (Dube et al., 2019; Bassier et al., 2022). While these non-experimental studies examine the effect of wage differentials on quit elasticity, they do not consider non-wage amenities.⁴ With our dataset, we can provide a more comprehensive view of compensation for labor services. Moreover, we offer a long-term perspective on starting a job under specific monopsony conditions.⁵

Finally, our paper contributes to the literature on upskilling and overeducation. Upskilling (Modestino et al., 2020; Deming, 2017; Deming and Kahn, 2018; Hershbein et al., 2018) refers to the idea that labor market concentration may enable firms to demand higher or better skills. Existing studies have explored how factors like the availability of workers - such as following the economic shock of the Great Recession (Hershbein and Kahn, 2018) or troop withdrawals (Modestino et al., 2020) - affect firms' skill demands. These studies typically find that an increase in worker availability leads to a higher demand for skills. We contribute to this discussion by focusing specifically on monopsonistic labor markets, distinguishing between knowledge-based skills, soft skills, and routine, lower-productivity basic skills. In this sense, we also contribute to existing research that explores the relationship between monopsony power and productivity (Bachmann et al., 2023).

Our paper is structured as follows: A detailed description of the data will be given in Section 2, as well as the definition of local labor markets and the calculation of the Herfindahl-Hirschman Index. In Section 3 we introduce the empirical strategy, and the main results are discussed in Section 4. Section 5 concludes the study.

2 Data

We use two main sets of data. The first one is administrative data provided by the *Austrian Employment Office* (Arbeitsmarktservice, AMS). This is a public employment service provider in the Austrian labor market that helps to match employees to vacancies, as well as supporting the unemployed and firms with advice, information, and financial support. These data cover more than 60% of all vacancies in Austria, the representation is particularly good at the lower level of positions.

³See Bachmann et al. (2023), Hirsch et al. (2010) or Hirsch et al. (2018) for monopsonistic labor market outcomes for the German labor market.

⁴Due to data limitations, most existing studies are unable to explore the relationship between monopsony power and non-wage amenities.

⁵See Wachter (2020) and Fruehwirth-Schnatter et al. (2012) on the importance of early-career conditions for later labor market outcomes.

The data are available for the time period 2002 until 2018, where each observation corresponds to an employer’s order. An order is for one or more vacancies, containing information about the searching firm, the number of workers wanted, industry and occupation, and, among other characteristics, the skill requirements. On average, about 61,000 firms are posting a total of 250,000 vacancies each year at the AMS. This set of data is used for the calculation of labor market concentration, as well as for estimating the effect of labor market concentration on the firms’ skill requirements.

The vacancy data are particularly rich, because they provide both 4-digit occupation and NACE-industry codes so that we can effectively look at the same jobs. Moreover, we have access to the full job announcement in detail: the full text of the announcement as well as a number of additional coded variables – like qualifications, job requirements as well as other amenities. After 2011, a new Equal Treatment Law in Austria required firms to post wage information for each job vacancy. Unlike in some U.S. states, the posted minimum wage cannot be an interval; it must reflect the wage that can reasonably be expected for the duties outlined in the job advertisement, and it cannot be lower than the wage specified in the relevant collective bargaining agreement. [Frimmel et al. \(2023\)](#) provide an extensive discussion of this reform.

The individuals and firms in the vacancy data can be directly matched with the *Austrian Social Security Database* (ASSD), which includes administrative records to verify pension claims and are structured as a matched employer-employee data set. These data cover all Austrian workers and provide detailed information on daily labor market activity. Information on individual earnings is available on an annual basis per employer. The data lacks information on the number of contracted hours, so we can only look at daily earnings. The ASSD allows us to obtain our outcome variable of interest (realized daily earnings). We further draw on the ASSD to include information on the individuals’ labor market history before they start the new job. The firm characteristics and employee demographics are used to enrich the information from the vacancy data.

The AMS data show which person applied for a vacancy and which person actually got hired. This applies only to persons who got their job directly via the AMS. There is a variable in both the AMS and ASSD data uniquely identifying a job posting. Using this variable, we connect both sources and analyze the effect of labor market concentration on both posted and actual wages of 105,150 individuals from this vacancy-employer-employee data set.

2.1 Sample selection

For the analysis, we only use vacancies of firms operating in the Austrian private sector between 2012 and 2017, as data for posted wages are fully available for this time period only.⁶ Thus, vacancies in e.g., public administration, military, health care, etc. are not considered in the calculation of labor market concentration. We additionally drop other non-governmental organizations, such as libraries, the whole arts industry, and home production.

We will later define labor market concentration at an occupational and regional level; i.e. whether there is a local concentration of employers searching for workers of a very specific

⁶Only after 2011, all firms were posting the minimum wage in job vacancy advertisements as required by a new Equal Treatment Act.

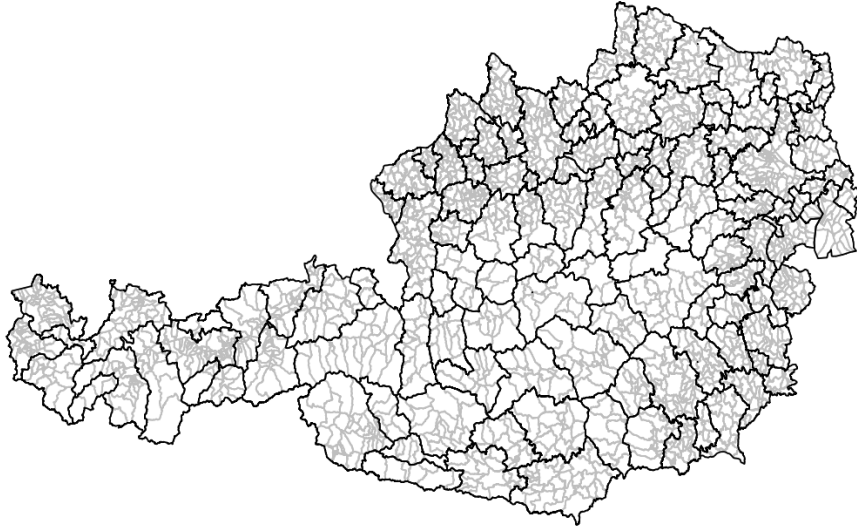
occupation. Therefore, we only keep occupation-commuting zone-year combinations when at least five vacancies are posted in a cell. This excludes thinly populated (rural) labor markets, where typical monopsony definitions would not work, i.e. a market with only one vacancy (from one firm) in a year leading to a measured full concentration.

2.2 Defining local labor markets

Following [Tolbert and Sizer \(1996\)](#) and [Dorn \(2009\)](#) we use commuting zones as our indicator for a local labor market, which is less arbitrary than using political districts. The construction of commuting zones requires data on bi-directional commuting ties between municipalities. This data is taken from the register-based Austrian census 2011 (available at Statistics Austria), and includes detailed information on municipality-to-municipality commuting flows (commuting matrix). A Hierarchical Cluster Algorithm is then applied to this commuting matrix to filter out which communities belong together. This algorithm clusters elements of the matrix based on their average distance from each other. Workers are assumed to move within these geographical areas, but not across borders.⁷ We follow [Bekhtiar \(2025\)](#) which defines differently-sized commuting zones for different average between-cluster distances. We use the 0.9875 distance measure resulting in 124 commuting zones.

Figure 1 shows how Austria is parted into 124 commuting zones, indicated by the black lines. Within these areas, the communities covered are outlined in gray.

Figure 1: Commuting zones



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^aNotes: This graph was constructed by Karim Bekhtiar using Austrian census 2011 data available at Statistik Austria to construct the commuting zones. The black lines indicate the 124 commuting zones, whereas the gray lines represent the community borders.

⁷Thanks to Karim Bekhtiar for providing us with these data ([Bekhtiar, 2025](#)).

2.3 Defining monopsony power

We follow [Azar et al. \(2020\)](#) and define a market where we assume competition between firms over workers as a local occupation-specific labor market on the commuting zone-by-4-digit ISCO occupation levels by year.⁸ We then obtain our baseline measure of concentration in a local labor market as the Herfindahl-Hirschman Index (HHI) calculated as the share of vacancies of all firms in that particular market. More precisely, let $J_{o,c,t}$ be the set of firms, operating in commuting zone c , posting a specific 4-digit (ISCO) occupation o in time t .

Denote by $N_{j,o,c,t}$ the number of postings for such a firm and occupation. The market share for firm j is then

$$s_{j,o,c,t} = \frac{N_{j,o,c,t}}{\sum_{k \in J_{o,c,t}} N_{k,o,c,t}} \quad (1)$$

From this market share, we can then calculate the Herfindahl-Hirschman Index (HHI) for each cell built by commuting zone c occupation o at time t as the sum of the squared market shares

$$HHI_{o,c,t} = \sum_{j \in J_{o,c,t}}^N (s_{j,o,c,t})^2 \quad (2)$$

Using job vacancies rather than employment to construct a measure of labor market concentration arguably reflects better how likely searching workers, both employed and unemployed, receive a job offer.⁹ Expressed differently, our index reflects concentration in the market share of firms hiring in a certain region and occupation, and therefore their power to "buy" work.¹⁰ Using vacancies rather than employment can also better reflect firms' market power in times of lower employee transitions and when jobs are vacated less frequently. Basing the concentration measure on vacancies then reflect the power of the very few firms hiring. Wages of newly hired workers may also be more sensitive to conditions in the local labor market.

One important implicit assumption for $HHI_{o,c,t}$ to capture market power is that workers cannot frictionless transit between local labor markets. However, there is strong evidence that workers face substantial obstacles associated with transitioning between labor markets in reality (e.g. [Traiberman, 2019](#)) and that job search behavior is quite local ([Manning and Petrongolo, 2017](#)). In addition, there is empirical evidence that workers are in general not well informed about their potential outside options ([Jäger et al., 2024](#)).

Almost all studies defined monopsony at an occupational and not an industrial level¹¹; because at an industry level there are many jobs or occupations, which makes the construction of comparable jobs difficult. Moreover, simple measures of the number of competitors do not necessarily provide a clear index of market power; similar to IO we use the Herfindahl-Hirschman

⁸[Azar et al. \(2020\)](#) choose a finer definition of a local labor market for the US: commuting zone-by-occupation at the 6-digit level. However, as the Austrian labor market is much smaller we would have ended up with many local labor markets with a zero number of vacancies. Therefore, we use a more aggregated definition of local labor markets in our work.

⁹Using job postings to measure concentration has also been used in, for example, [Azar et al. \(2020\)](#), [Marinescu et al. \(2021\)](#), and [Azar et al. \(2024\)](#).

¹⁰For a recent discussion, see, [Bassier et al. \(2022\)](#)

¹¹Exceptions like [Rinz \(2022\)](#), [Berger et al. \(2022\)](#) and [Benmelech et al. \(2022\)](#) defined them by 3-digit and 4-digit industries, mainly because occupations were not available in their data

index (HHI) (Berry et al., 2019). Oberfichtner and Popp (2025 forthcoming) provide detailed estimates about the extent of labor market concentration in Germany, showing, in particular, that concentration is larger in occupations with more complex jobs.

2.4 Required skills

Following Aghion et al. (2019), we created several categories of skills, including knowledge-based skills, soft skills, and basic skills. According to their framework, certain skills are observable and can be easily associated with wage determination based on those qualifications. However, some skills, particularly those that are less observable, play a crucial role in influencing wages, especially in jobs that require significant interaction with other people.

We created these skill measures by utilizing the full text of the job advertisements. First, ten students (including ourselves) coded 200 random advertisements looking for exact words as well as synonyms for these categories. Then, a simple machine-learning algorithm was used to calculate these categories for all vacancies.¹²

The knowledge-based skills category includes variables such as *finance* (e.g., analytical know-how), *computer and IT* (e.g., programming), *project management* (e.g., negotiation, scheduling), and *problem-solving* (e.g., identifying and resolving issues). These represent technical and cognitive skills critical for many jobs.

The soft skills category, on the other hand, captures interpersonal and personal traits, including *social skills* (e.g., cooperation, conflict resolution), *character traits* (e.g., responsibility, hard-working), and *customer service skills* (e.g., communication, adaptability). These are important for roles requiring interaction with others.

The basic skills category focuses on fundamental abilities, including *manual and physical tasks* (e.g., strength, woodworking), *routine tasks*, and *writing skills*, reflecting more practical or task-oriented job requirements.

The knowledge-based skills variable is constructed by summing the number of relevant skills mentioned in the job posting, ranging from 0 to 4. A higher value indicates that more knowledge-based skills are associated with the job. If none of the skills are mentioned, the variable is 0. If one skill is mentioned, the value is 1, and so on, up to a maximum of 4 when all four skills are present. A similar approach is used for constructing soft skills and basic skills, where a higher value indicates that more relevant skills are associated with the job.

In addition to skill categories, the postings provide insights into benefits, a combination of *non-monetary benefits* (e.g., flexible work arrangements, autonomy, a firm canteen or child care possibilities), a *good work climate*, *reputable employers*, and *favorable contract terms* (e.g., open-ended contracts).

2.5 Descriptive statistics

The descriptive statistics in Table 1 provide a comprehensive overview of the key variables in the analysis. Mean labor market concentration in Austria is 0.07 and around 6% of all our local labor markets have a HHI above 0.25 and therefore can be considered medium- to highly

¹²Thanks to Kajetan Schweighofer for implementing the machine-learning algorithms.

concentrated. The distribution is shown in Figure 2. Compared with other countries, such as France and the USA (Macaluso et al., 2019; Marinescu et al., 2021), Austria exhibits lower labor market concentration.

This indicates that some markets are highly concentrated, while others have low concentration, showing economic diversity. To exclude outliers, we drop the 5% lowest and 1% highest of daily wages in both actual and posted wages. After applying the trimming, the gross daily wage, representing the earnings of new hires, ranges from 18.44 to 120.07, indicating the inclusion of both full-time and part-time workers in the sample.¹³ In contrast, the posted daily wage, reflecting employers’ advertised pay, spans a broader range, from 11.05 to 205.48, highlighting potential discrepancies between advertised and realized earnings.¹⁴ Individual-level characteristics reveal a balanced and representative dataset. The sample comprises 105,150 individuals, with an average age of 39 years and a gender distribution almost evenly split between males and females. Additionally, 92% of the individuals are Austrian nationals, offering a predominantly local perspective. Workers included in the analysis are between 22 and 66 years old, capturing a critical segment of the active labor force. The job postings in the dataset provide detailed information on skill requirements and job characteristics, which were grouped into three main categories: knowledge-based skills, soft skills, and basic skills, alongside job-related benefits which were mentioned only in 103,855 vacancies.

Table 1: Descriptive statistics

	Count	Min.	Max.	Mean	Std.Dev.
Labor market concentration	105,150	.0019083	1	0.07	0.11
Gender	105,150	0	1	0.53	0.50
Austrian	105,150	0	1	0.92	0.28
Educational level	105,150	1	5	2.23	1.06
Age	105,150	22	66	38.87	10.10
Gross daily wage	105,150	18.44	120.07	61.45	20.75
Posted daily wage	105,150	11.05	205.48	52.35	10.55
Knowledge-based skills	103,855	0	4	0.28	0.63
Soft skills	103,855	0	3	0.91	0.94
Basic skills	103,855	0	3	0.84	0.95
Benefits	103,855	0	4	0.57	0.76

Notes: This table presents descriptive statistics for the key variables in the analysis. The variables include labor market concentration, demographic characteristics (gender, Austrian citizenship, educational level, and age), wage measures (gross and posted daily wages), and job-related skills and attributes (knowledge-based skills, soft skills, basic skills and benefits). This table was constructed using the AMS and the ASSD data.

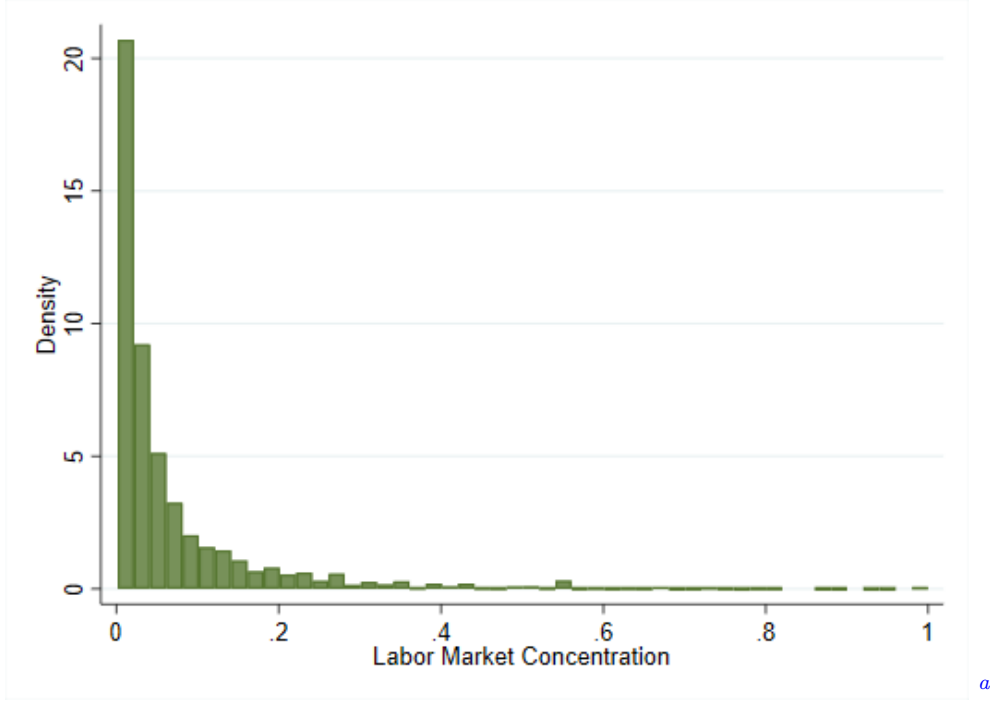
3 Empirical Approach

Having defined our measure of labor market concentration, we run a set of regressions to assess how concentration affects firms’ posting behavior and workers’ wages.

¹³The 5th and 99th percentile correspond to daily wages of 28,59 Euros and 112,84 Euros/day respectively.

¹⁴Posted wages can include bonuses, commissions or other type of monetary benefits which are part of the actual wage calculation.

Figure 2: Distribution of labor market concentration



^aNote: This figure depicts the distribution of the Herfindahl-Hirschman Index and was constructed using the AMS data.

Using our matched vacancy-employer-employee data, our main specification is

$$o_{e,j,o,c,t} = \alpha + \beta * \log(HHI_{o,c,t}) + X'_{e,j,t} * \Gamma + \Omega_o + \zeta_c + \Phi_t + \varepsilon_{e,j,o,c,t} \quad (3)$$

where $o_{e,j,o,c,t}$ is the outcome of interest – either log-posted and actual wages, or amenities/skill requirements – for an individual e filling a position at firm j , in occupation o and commuting zone c at time t . We include a set of worker and firm characteristics $X'_{e,j,t}$ in our estimation to capture potential worker-firm match effects unrelated to labor market concentration. Specifically, worker characteristics include age, age², gender, nationality as well as education. Firm characteristics include firm size and 4-digit (NACE) industry fixed effects. In addition, we control for occupation (Ω_o), commuting zones (ζ_c) and time (Φ_t) fixed effects.

Our main identifying assumption is an occupation-location-time fixed-effects model. Through four-digit occupation fixed effects we only compare individuals within the same occupation where labor market concentration changes over space and time. The identification assumption is, thus, that wages have a common time, location and occupation trend.

If labor markets are frictionless and all workers can move to perfectly competitive labor markets, then we would not expect to see any effects. However, the impact on non-wage amenities is a priori ambiguous and depends on whether workers view these amenities as complements or substitutes. The coefficient β on our variable of interest $\log(HHI_{o,c,t})$ represents an estimate of the wage elasticity when considering the impact of concentration on (log) wages. We discuss effect sizes in terms of a one standard deviation increase of $\log(HHI_{o,c,t})$ when considering non-wage amenities and skill requirements.

4 Empirical Results

4.1 The impact of labor market concentration on wages and job amenities

In this section, we first discuss the impact of labor market concentration on postings and starting wages. Then, we explore whether initial exposure to higher concentrated labor markets can impact the long-term careers of workers. Lastly, we assess whether labor market concentration leads firms to adjust on other margins than wages.

Initial Impact: Table 2 presents the regression results examining the impact of labor market concentration on posted and realized wages. Here, we start with estimates controlling only for occupation fixed effects, thus looking at within-occupation effects of labor market concentration, then we proceed with a more demanding specification, controlling also for commuting zone, year, industry fixed effects as well as for effects of education and firm size.

Table 2: Impact of labor market concentration on posted and actual wages

	log(Posted Wages)	log(Posted Wages)	log(Actual Wages)	log(Actual Wages)
<i>log(Labor market concentration)</i>	-0.00781*** (0.00196)	-0.01577*** (0.00340)	-0.03236*** (0.00507)	-0.03489*** (0.00813)
<i>Age</i>	0.00731*** (0.00092)	0.00277*** (0.00082)	0.00415* (0.00225)	0.00057 (0.00215)
<i>Age²</i>	-0.00008*** (0.00001)	-0.00003*** (0.00001)	-0.00002 (0.00003)	0.00002 (0.00003)
<i>Gender</i>	-0.04683*** (0.00776)	-0.03895*** (0.00601)	-0.22424*** (0.01890)	-0.20067*** (0.01334)
<i>Austrian</i>	0.00819*** (0.00216)	0.00154 (0.00217)	0.00394 (0.00732)	-0.00011 (0.00665)
Education FE	No	Yes	No	Yes
Firm Size FE	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes
Occupation FE	Yes	Yes	Yes	Yes
Commuting Zone FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Mean of LHS ^a variable	52.35	52.35	61.45	61.45
Observations	105,150	105,150	105,150	105,150
Adjusted R-squared	0.382	0.484	0.366	0.422

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

Notes: This table presents the impact of log(labor market concentration) on both posted and actual wages (log-transformed). It includes results for posted wages in Columns (1)-(2) and for actual wages in Columns (3)-(4). Columns (1) and (3) include only occupation-fixed effects, while Columns (2) and (4) include all fixed effects such as Education, Firm Size, Industry, Occupation, Commuting Zone, and Year-fixed effects. Standard errors are clustered at occupation level.

^aMean of Left Hand Side (LHS) variable in regression: in Cols (1) - (2) it refers to mean of posted wage, whereas in Cols (3) - (4) it is mean of actual wage

In all of these specifications, we find results consistent with the hypothesis that more monopsony power affects firms' wage posting decisions and workers' wages. The results in Columns (2) and (4) imply significantly negative posting and wage elasticities of -0.0158 and -0.0349 respectively. These impacts are substantial. Interestingly, while workers in Austria generally face lower labor market concentration, its impact on wages seems to be much higher than in other countries. For example, for France [Marinescu et al. \(2021\)](#) find an elasticity between -0.002 and -0.013 .

An additional implication of our results in Table 2 is that lower wages due to high monopsony power are driven by reduced workers' bargaining power rather than through the firm's wage posting channel. This follows from comparing similar workers hired for similar jobs, while some

differ in their exposure to labor market concentration. Algebraically, actual wages are posted wages plus a mark-up due to the bargaining power of the employee. Therefore, the difference between the monopsony effect of actual wages and the monopsony effect of posted wages is the impact of monopsony on workers' bargaining power. The elasticity of bargaining power is -0.0191 ¹⁵, which is larger than the elasticity of the posted wages of -0.0158 .

Tables 3, 4 and 5 show similar results, concentrating on differences between young and old, men and women and Austrian or non-Austrians. Here we see that higher labor market concentration has a substantially larger impact on older workers, women, and non-Austrians, in line with previous evidence (e.g., Winter-Ebmer, 1995).

While elderly workers, women and non-Austrians are generally more disadvantaged - as compared to the respective other groups - bargaining power in a more concentrated market suffers more for young workers, women and non-Austrians. This reverse effect for young workers may be due to their less experienced position in the labor market.

Table 3: Labor market concentration and earnings by age group

	$\log(\text{Posted Wages})$ (≥ 37)	$\log(\text{Actual Wages})$ (≥ 37)	$\log(\text{Posted Wages})$ (< 37)	$\log(\text{Actual Wages})$ (< 37)
$\log(\text{Labor market concentration})$	-0.01568*** (0.00326)	-0.03871*** (0.00876)	-0.01598*** (0.00378)	-0.02991*** (0.00813)
<i>Gender</i>	-0.04204*** (0.00643)	-0.21296*** (0.01710)	-0.03435*** (0.00600)	-0.19184*** (0.01182)
<i>Austrian</i>	0.00134 (0.00239)	0.00022 (0.00690)	0.00046 (0.00292)	-0.00536 (0.00698)
Education FE	Yes	Yes	Yes	Yes
Firm Size FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	57,301	57,301	47,849	47,849
Adjusted R-squared	0.506	0.423	0.463	0.425

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

Notes: This table presents the relationship between $\log(\text{labor market concentration})$ and earnings, segmented by median age. Columns (1) - (2) show the impact of labor market concentration on posted and actual wages respectively for older individuals, while Columns (3) and (4) focus on individuals aged below 37. Control variables include gender, Austrian citizenship status, and fixed effects for education, firm size, industry, occupation, commuting zone, and year. Standard errors are clustered at occupation level.

Long-Term Effects: Our matched data allows us to explore the long-term impacts of initial exposure to labor market concentration. To do this, we fix the HHI index at the initial commuting zone c and occupation o level but allow the worker to change occupation and/or commuting zone later on.¹⁶

In Figure 3, we plot the coefficients from ten separate year-by-year regressions, where realized log wages are regressed on the initial HHI index and our controls, as defined in Equation 3, along with 95% confidence intervals. As a reference point, we also include the initial impact on wages from Table 2. The detailed results underlying the figure are provided in the appendix.

Two interesting features emerge from the figure. On the one hand, the impact of initial exposure to labor market concentration tends to fade over time. For example, the estimated

¹⁵0.03489-0.01577

¹⁶In our data, only the occupation of the worker's initial employment spell is recorded, so we cannot explore whether switching occupations could be beneficial.

Table 4: Labor market concentration and earnings by gender

	<i>log(Posted Wages)</i> Male	<i>log(Actual Wages)</i> Male	<i>log(Posted Wages)</i> Female	<i>log(Actual Wages)</i> Female
<i>log(Labor market concentration)</i>	-0.01546*** (0.00441)	-0.02456*** (0.00690)	-0.01525*** (0.00310)	-0.03864*** (0.00987)
<i>Age</i>	0.00422*** (0.00085)	0.01454*** (0.00190)	0.00146 (0.00093)	-0.01327*** (0.00247)
<i>Age</i> ²	-0.00004*** (0.00001)	-0.00016*** (0.00002)	-0.00002* (0.00001)	0.00019*** (0.00003)
<i>Austrian</i>	0.00440 (0.00360)	0.00840 (0.00753)	-0.00029 (0.00291)	-0.01269** (0.00542)
Education FE	Yes	Yes	Yes	Yes
Firm Size FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	49,912	49,912	55,238	55,238
Adjusted R-squared	0.444	0.342	0.457	0.271

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

Notes: This table examines the relationship between $\log(\text{labor market concentration})$ and earnings, segmented by gender. Column (1) - (2) present the regression results for male for posted and actual wages respectively, while Columns (3) and (4) report results for female for the same type of wages. Control variables include age, Austrian citizenship status, and fixed effects for education, firm size, industry, occupation, commuting zone, and year. Standard errors are clustered at occupation level.

Table 5: Labor market concentration and earnings by nationality

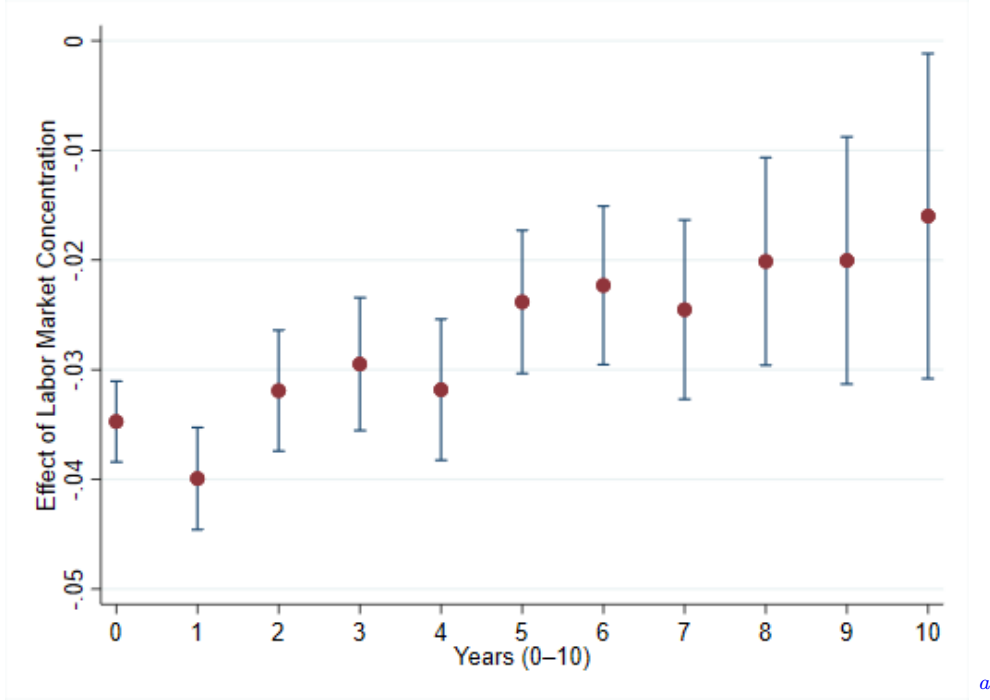
	<i>log(Posted Wages)</i> Austrians	<i>log(Actual Wages)</i> Austrians	<i>log(Posted Wages)</i> Non-Austrians	<i>log(Actual Wages)</i> Non-Austrians
<i>log(Labor market concentration)</i>	-0.01609*** (0.00341)	-0.03412*** (0.00818)	-0.01291** (0.00610)	-0.03939*** (0.01245)
<i>Age</i>	0.00310*** (0.00086)	0.00049 (0.00222)	-0.00049 (0.00087)	-0.00023 (0.00256)
<i>Age</i> ²	-0.00003*** (0.00001)	0.00002 (0.00003)	0.00001 (0.00001)	0.00002 (0.00003)
<i>Gender</i>	-0.03959*** (0.00610)	-0.20356*** (0.01328)	-0.03056*** (0.00436)	-0.16654*** (0.01362)
Education FE	Yes	Yes	Yes	Yes
Firm Size FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	96,268	96,268	8,882	8,882
Adjusted R-squared	0.479	0.423	0.547	0.415

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

Notes: This table examines the relationship between $\log(\text{labor market concentration})$ and earnings, segmented by nationality. Columns (1) - (2) present the effect of labor market concentration on the posted and actual wages of Austrian citizens, while Columns (3) and (4) report results for non-Austrian's posted and actual wages, respectively. Control variables include age, gender, and fixed effects for education, firm size, industry, occupation, commuting zone, and year. Standard errors are clustered at occupation level.

coefficient 10 years after the initial exposure is roughly half the magnitude of the impact when initially hired. On the other hand, recovery from initial exposure occurs only slowly, and even after 10 years, workers initially exposed to more concentrated labor markets continue to earn significantly lower wages.

Figure 3: Effect of labor market concentration on future wages



^aNote: This graph depicts the impact of the Herfindahl-Hirschman Index ($\log(\text{HHI})$) on wages over a 10-year period. The points represent the estimated effects, while the error bars denote the 95% confidence intervals. The data was derived from matched AMS-ASSD records.

Our estimates here are in line with recent findings that initial conditions in the local labor market can impact workers' long-term career prospects (e.g., [Kahn, 2010](#); [Garin and Rothbaum, 2024](#)), although workers in our sample tend to be older and more experienced. The results show that labor market concentration can have long-term adverse effects on workers, even when workers can move markets. In the next section, we explore whether these long-run effects could be related to skills and skill development.

Non-Wage Amenities: Jobs differ in many dimensions that determine their attractiveness to workers, with wages being just one of them. How firms design their jobs has important implications for hiring and retaining workers, and may also differ by labor market concentration. We explore how labor market concentration is associated with the provision of non-wage amenities, such as flexible working time or a firm canteen, by the firm. Together with the wage estimates from the previous section, this allows us to assess whether wages and non-wage amenities are regarded as complements or substitutes and whether workers in monopsonistic labor markets experience additional lower welfare by the under-provision of such amenities.¹⁷

The results are presented in Table 6. Column (1) examines the effect of monopsony power on

¹⁷[Dube et al. \(2022\)](#) and [Lamadon et al. \(2022\)](#) provide a thorough discussion of the relationship of compensating differentials in monopsonistic labor markets.

whether a firm offers any non-wage amenities, using a binary indicator as the outcome. In Column (2), we measure the number of amenities provided. The results clearly show that firms in monopsonistic labor markets are less likely to offer non-monetary amenities and fewer amenities overall. Both estimates are statistically significant and of considerable magnitude. For example, an increase of the HHI by one standard deviation or roughly 0.11 log points decreases the likelihood that a firm offers any non-wage benefits by around 0.6 percentage points.¹⁸ Similarly, the number of amenities provided by firms decreases by around 0.01. Together with our estimates for wages, the results imply that non-monetary amenities and wages are complements. They also imply that non-monetary amenities are underprovided in monopsonistic labor markets.

Table 6: Labor market concentration and benefits

	(1)	(2)
	Any benefits offered	Number of benefits offered
<i>log(Labor market concentration)</i>	-0.05113*** (0.01306)	-0.05710*** (0.01805)
Firm Size FE	Yes	Yes
Industry FE	Yes	Yes
Occupation FE	Yes	Yes
Commuting Zone FE	Yes	Yes
Year FE	Yes	Yes
Mean of LHS variable	0.40	0.57
Observations	103,855	103,855
Adjusted R-squared	0.1688	0.1468

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

Notes: This table shows the effect of $\log(\text{labor market concentration})$ measured as $\log(\text{HHI})$ on benefits offered. Each observation corresponds to a job posting. Column 1 estimates the effect of labor market concentration on whether a firm offers any non-wage amenities, using a binary indicator as the outcome and Column 2 examines the effect of labor market concentration on the number of amenities provided. Both specifications include fixed effects for firm size, industry, occupation, commuting zone, and year. Standard errors are clustered at occupation level.

4.2 The Impact of labor market concentration on skill requirements

We further explore whether monopsony power influences firms' skill requirements, distinguishing between knowledge-based skills (e.g., problem-solving and project management), soft skills (e.g., social skills), and basic skills, which relate to more routine, lower-productivity work.

On the one hand, monopsonistic firms may "upskill" their workforce, requiring greater knowledge-based or soft skills, as suggested by [Modestino et al. \(2020\)](#). This may be a further consequence of labor market concentration: monopsonists pay less and require better workers. On the other hand, it could be that monopsonistic firms offer fewer opportunities for skill development, as they often rely on outdated and inefficient production methods, thus demanding more basic skills. For example, [Bachmann et al. \(2023\)](#) shows that monopsonistic firms tend to be both small and unproductive. Additionally, [Arellano-Bover \(2024\)](#) finds that firm size at the first job influences long-run labor market outcomes, with smaller firms offering fewer

¹⁸From Table 1, the standard deviation of the HHI is 0.11. Then, a one standard deviation increase in the HHI reduced the likelihood of offering any amenities by $\log(1.11) \cdot -0.05113 = 0.0048$.

opportunities for skill development.¹⁹

Our estimation results are presented in Table 7. Columns (1) to (3) report the impact of monopsony power on whether any skill from each respective category is required (using binary indicators). Columns (4) to (6) show the effect on the number of specific skills required.

Table 7: Labor market concentration and skill requirements

	Skill Required			Skill Intensity		
	Knowledge-based	Soft	Basic	Knowledge-based	Soft	Basic
$\log(\text{Labor market concentration})$	0.00228 (0.00437) ^a [0.00221] ^b	0.00408 (0.01049) [0.00306]	0.01642 (0.01112) [0.00304]	-0.00210 (0.00560) [0.00329]	-0.00078 (0.01683) [0.00557]	0.02577 (0.02055) [0.00569]
Mean of LHS variable	0.20	0.58	0.48	0.28	0.91	0.84
Observations	103,855	103,855	103,855	103,855	103,855	103,855
Adjusted R-squared	0.3676	0.1973	0.2451	0.4064	0.2538	0.2713
Firm Size FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in squared brackets, and clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: This table examines the effect of $\log(\text{labor market concentration})$ on firms' skill requirements. Columns 1-3 show the impact of labor market concentration on whether any skill from each respective category is required using binary indicators. Columns 4-6 show the effect of labor market concentration on the number of specific skills required. All specifications include fixed effects for firm size, industry, occupation, commuting zone, and year. Standard errors clustered at occupation level.

^aClustered standard errors

^bRobust standard errors

We do not find evidence for the upskilling theory, neither for the requirement of any knowledge-based or soft skills - see Columns (1) and (2) - nor for the number of such skills required - see Columns (4) and (5).²⁰ In contrast, firms in monopsonistic labor markets are significantly more likely to demand basic skills and also more of those, see Columns (3) and (6), if we consider robust standard errors. For example, an increase in the HHI index from the 25th to the 75th percentile increases the probability requiring basic skills by around 3 percentage points if we analyze it with robust standard errors. However, when analysis is done with clustered standard errors at occupational level we see no significant effect of labor market concentration on any skills. Although we cannot directly investigate whether higher demand for basic and ultimately lower-productivity skills drives our long-term wage estimates from the previous section, the results suggest that workers may be disadvantaged in monopsonistic markets as firms become less efficient due to underinvestment in relevant skills.

5 Conclusion

This paper investigates the impact of labor market concentration on wages and skill requirements in Austria, using administrative data from the Austrian Employment Office (AMS) and the Austrian Social Security Database (ASSD). By constructing the Herfindahl-Hirschman Index

¹⁹Arellano-Bover (2024) does not investigate the role of monopsonistic labor markets in his study.

²⁰Related to these results Macaluso et al. (2019) and Qiu and Sojourner (2023) find that firms in monopsonistic markets are not able to hire higher-skilled workers at lower wages.

(HHI) to measure labor market concentration, we explore how monopsony power affects both posted and realized wages, non-wage job amenities, as well as job skill requirements.

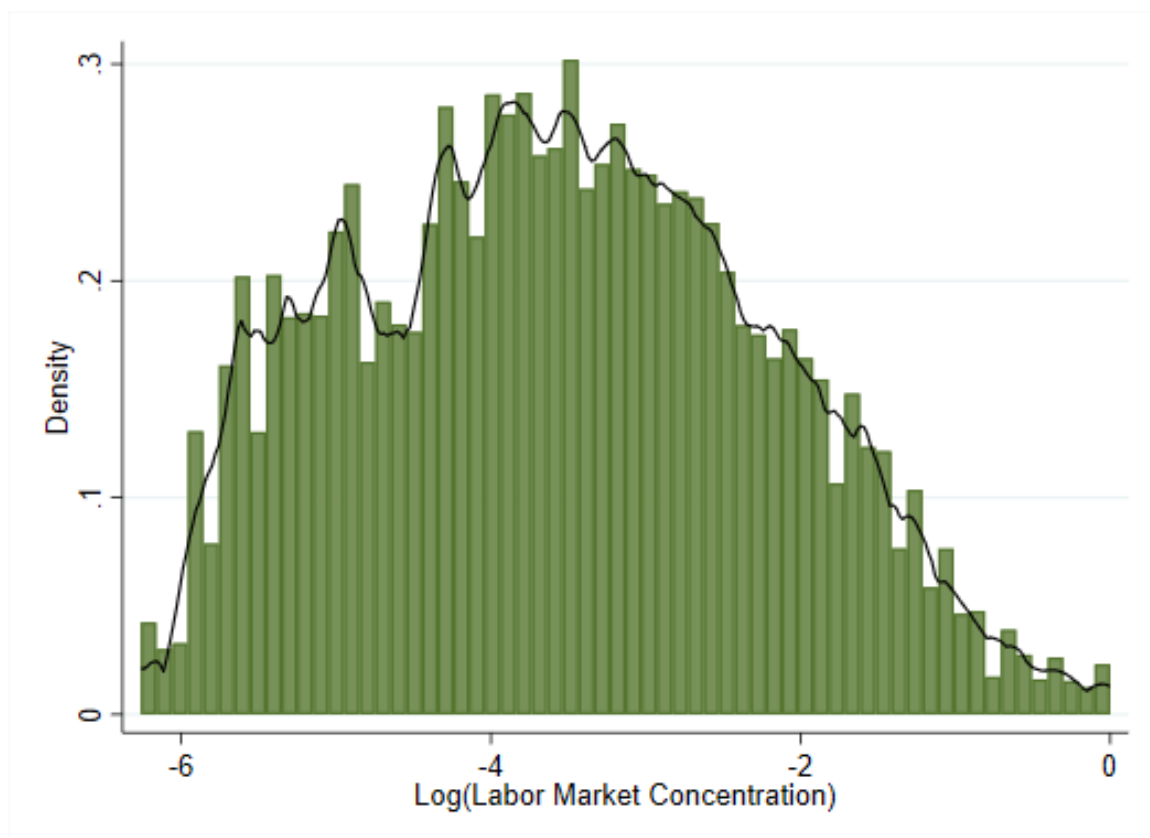
Our findings demonstrate that labor market concentration significantly reduces both posted and actual wages. Specifically, a 10% increase in HHI results in a 0.16% reduction in posted wages and a 0.35% reduction in actual wages, highlighting the monopsony power of employers in concentrated labor markets. Thus, a larger part of this disadvantage for workers comes from the impact on monopsony power on direct bargaining power of the workers. This effect persists over a decade, though the magnitude diminishes slightly over time.

Moreover, concentrated labor markets are associated with higher demand for basic skills, whereas the impact on knowledge-based and soft skills is negligible. This indicates that monopsony power enables firms to demand more from employees without corresponding compensation. Additionally, concentrated markets reduce the provision of non-wage benefits, further highlighting the negative implications for workers.

Our results complement those of [Azar et al. \(2020\)](#), [Marinescu et al. \(2021\)](#), and [Benmelech et al. \(2022\)](#). These papers consistently find that increased labor market concentration reduces the wages of workers. This result suggests that the bargaining power of employees is weak due to increased labor market concentration and that this is the reason why they might not be able to benefit from increased productivity in terms of higher wages. This emphasizes the importance of the role of concentration and bargaining positions of employers and employees. In this context, antitrust authorities should incorporate consequences of firm entries and exits on labor market concentration, to restore the balance and improve the bargaining power of employees.

A Appendix

Figure A.1: Distribution of labor market concentration



^aNotes: This graph was constructed using the AMS data, whereas each observation corresponds to a vacancy. The Herfindahl-Hirschman Index was log-transformed as the data was skewed and had many outliers. A log transformation makes the data more symmetric, which is shown in this figure.

Table A.1: Regression results for wages, year 1-5

	(1)	(2)	(3)	(4)	(5)
	$\log(\text{Actual Wages})_1$	$\log(\text{Actual Wages})_2$	$\log(\text{Actual Wages})_3$	$\log(\text{Actual Wages})_4$	$\log(\text{Actual Wages})_5$
$\log(\text{Labor market concentration})$	-0.040*** (0.002)	-0.032*** (0.003)	-0.029*** (0.003)	-0.032*** (0.003)	-0.024*** (0.003)
Age	0.004*** (0.001)	0.010*** (0.001)	0.019*** (0.001)	0.028*** (0.001)	0.037*** (0.001)
Age^2	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)
Gender	-0.239*** (0.003)	-0.232*** (0.004)	-0.236*** (0.004)	-0.240*** (0.004)	-0.253*** (0.004)
Austrian	-0.001 (0.004)	0.005 (0.005)	0.009 (0.005)	0.014** (0.006)	0.018*** (0.006)
Observations	96,530	91,623	89,435	88,823	86,571
Adjusted R-squared	0.326	0.257	0.227	0.211	0.219
Education FE	Yes	Yes	Yes	Yes	Yes
Firm Size FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

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

Notes: This table presents regression results for log wages across five years. The dependent variable in each column is $\log(\text{Actual Wages})$, with Columns (1) through (5) showing wages from year 1 to year 5. The independent variable, $\log(\text{labor market concentration})$ indicates the negative impact of concentration on wages across all specifications. Control variables include age, gender, and nationality. The models also incorporate fixed effects for education, firm size, industry, occupation, commuting zone, and year. Standard errors are clustered at occupational level.

Table A.2: Regression results for wages, year 6-10

	(1)	(2)	(3)	(4)	(5)
	$\log(\text{Actual Wages})_6$	$\log(\text{Actual Wages})_7$	$\log(\text{Actual Wages})_8$	$\log(\text{Actual Wages})_9$	$\log(\text{Actual Wages})_{10}$
$\log(\text{Labor market concentration})$	-0.022*** (0.004)	-0.025*** (0.004)	-0.020*** (0.005)	-0.020*** (0.006)	-0.016*** (0.008)
<i>Age</i>	0.045*** (0.001)	0.046*** (0.002)	0.049*** (0.002)	0.052*** (0.002)	0.050*** (0.003)
<i>Age</i> ²	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
<i>Gender</i>	-0.254*** (0.005)	-0.245*** (0.005)	-0.240*** (0.006)	-0.262*** (0.007)	-0.294*** (0.009)
<i>Austrian</i>	0.025*** (0.006)	0.019*** (0.007)	0.020** (0.008)	0.029*** (0.010)	0.027** (0.012)
Observations	72,867	60,184	46,415	32,664	16,356
Adjusted R-squared	0.216	0.210	0.213	0.235	0.286
Education FE	Yes	Yes	Yes	Yes	Yes
Firm Size FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

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

Notes: This table presents regression results for log wages across five years. The dependent variable in each column is log wages, with Columns (1) through (5) showing wages from year 6 to year 10. The independent variable $\log(\text{labor market concentration})$ indicates the negative impact of concentration on wages across all specifications. Control variables include age, gender, and nationality. The models also incorporate fixed effects for education, firm size, industry, occupation, commuting zone, and year. Standard errors are clustered at occupational levels.

References

- Abel, Guy and Uwe Sunde (2018), ‘Wage dynamics and labor market concentration in the UK private sector’, *European Economic Review* **109**, 96–115.
- Aghion, Philippe, Antonin Bergeaud, Richard Blundell and Rachel Griffith (2019), The innovation premium to soft skills in low-skilled occupations, Technical report, London School of Economics and Political Science, LSE Library.
- Anton, Jose-Ignacio, Rene Boeheim and Rudolf Winter-Ebmer (2022), ‘The effect of migration on unionization in austria’, *Empirical Economics* **63**(5), 2693–2720.
- Arellano-Bover, Jaime (2024), ‘Career consequences of firm heterogeneity for young workers: First job and firm size’, *Journal of Labor Economics* **42**(2), 549–589.
- Arnold, David (2019), ‘Mergers and acquisitions, local labor market concentration, and worker outcomes’, *Local Labor Market Concentration, and Worker Outcomes (October 27, 2019)* .
- Azar, José, Emiliano Huet-Vaughn, Ioana Marinescu, Bledi Tsaka and Till von Wachter (2024), ‘Minimum wage employment effects and labour market concentration’, *Review of Economics Studies* **91**(4), 1843–1883.
- Azar, José, Ioana Marinescu, Marshall Steinbaum and Taska Bledi (2020), ‘Concentration in US labor markets: Evidence from online vacancy data’, *Labour Economics* **66**, 101886.
- Bachmann, Ruediger, Christian Bayer, Heiko Stueber and Felix Wellschmied (2023), Monopsony makes firms not only small but also unproductive: Why east germany has not converged, Technical report, University of Bonn and University of Mannheim, Germany.
- Bassanini, Andrea, Cyprien Batut and Eve Caroli (2021), Labor market concentration and stayers’ wages: Evidence from France, Technical report, IZA Discussion Papers.
- Bassanini, Andrea, Giulia Bovini, Eve Caroli, Jorge Casanova Ferrando, Federico Cingano, Paolo Falco, Florentino Felgueroso, Marcel Jansen, Pedro S Martins, António Melo et al. (2024), ‘Labor market concentration, wages and job security in europe’, *Journal of Human Resources* .
- Bassier, Ihsaan, Arindrajit Dube and Suresh Naidu (2022), ‘Monopsony in movers - The elasticity of labor supply to firm wage policies’, *Journal of Human Resources* **57**(S), S51–S86.
- Bekhtiar, Karim (2025), ‘The Decline of Manufacturing Employment and the Rise of the Far-Right in Austria’, *Journal of Public Economics* .
- Benmelech, Efraim, Nittai K. Bergman and Hyunseob Kim (2022), ‘Strong employers and weak employees: How does employer concentration affect wages?’, *Journal of Human Resources* **57**(2), 468–504.
- Berger, David, Kyle Herkenhoff and Simon Mongey (2022), ‘Labor market power’, *American Economic Review* **112**(4), 1147–93.
- Berry, Steven, Martin Gaynor and Fiona Scott Morton (2019), ‘Do increasing markups matter? Lessons from empirical industrial organization’, *Journal of Economic Perspectives* **33**(3), 44–68.
- Card, David (2022), ‘Who set your wage?’, *American Economic Review* **112**(4), 1075–1090.
- Deming, David J (2017), ‘The growing importance of social skills in the labor market’, *The Quarterly Journal of Economics* **132**(4), 1593–1640.
- Deming, David and Lisa B Kahn (2018), ‘Skill requirements across firms and labor markets: Evidence from job postings for professionals’, *Journal of Labor Economics* **36**(S1), S337–S369.
- Dorn, David (2009), Essays on inequality, spatial interaction, and the demand for skills, PhD thesis, University of St. Gallen.

- Dube, Arindrajit, Laura Giuliano and Jonathan Leonard (2019), ‘Fairness and frictions: The impact of unequal raises on quit behavior’, *American Economic Review* **109**(2), 620–663.
- Dube, Arindrajit, Suresh Naidu and Adam D Reich (2022), Power and dignity in the low-wage labor market: Theory and evidence from Wal-Mart workers, Technical report, National Bureau of Economic Research, Inc.
- Frimmel, Wolfgang, Bernhard Schmidpeter, Rene Wiesinger and Rudolf Winter-Ebmer (2023), Mandatory wage postings, bargaining and the gender wage gap, Technical report, JKU Linz.
- Fruehwirth-Schnatter, Sylvia, Christoph Pamminger, Andrea Weber and Rudolf Winter-Ebmer (2012), ‘Labor market entry and earnings dynamics: Bayesian inference using mixtures-of-experts markov chain clustering’, *Journal of Applied Econometrics* **27**(7), 1116–1137.
- Garin, Andrew and Jonathan Rothbaum (2024), The long-run impacts of public industrial investment on local development and economic mobility: Evidence from World War II, Technical report, WE Upjohn Institute for Employment Research.
- Hershbein, Brad, Claudia Macaluso and Chen Yeh (2018), Labor market concentration and the demand for skills, in ‘IDSC of IZA Workshop: Matching Workers and Jobs Online’, pp. 2–6.
- Hershbein, Brad and Lisa B. Kahn (2018), ‘Do recessions accelerate routine-biased technological change? Evidence from vacancy postings’, *American Economic Review* **108**(7), 1737–1772.
- Hirsch, Boris, Elke J. Jahn, Alan Manning and Michael Oberfichtner (2022), ‘The urban wage premium in imperfect labor markets’, *Journal of Human Resources* **57**(S), S111–S136.
- Hirsch, Boris, Elke J. Jahn and Claus Schnabel (2018), ‘Do employers have more monopsony power in slack labor markets?’, *ILR Review* **71**(3), 676–704.
- 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.
- Izumi, Atsuko, Naomi Kodama and Hyeog Ug Kwon (2023), ‘Labor market concentration and heterogeneous effects on wages: Evidence from Japan’, *Journal of the Japanese and International Economies* **67**, 101242.
- Jäger, Simon, Christopher Roth, Nina Roussille and Benjamin Schoefer (2024), ‘Worker beliefs about outside options’, *Quarterly Journal of Economics* **139**(3), 1505–1556.
- Kahn, Lisa (2010), ‘The long-term labor market consequences of graduating from college in a bad economy’, *Labour Economics* **17**(2), 303–316.
- Kim, Myongjin, Qi Ge and Donggeun Kim (2021), ‘Mergers and labor market outcomes in the US airline industry’, *Contemporary Economic Policy* **39**(4), 849–866.
- Lamadon, Thibaut, Magne Mogstad and Bradley Setzler (2022), ‘Imperfect competition, compensating differentials, and rent sharing in the US labor market’, *American Economic Review* **112**(1), 169–212.
- Lipsius, Ben (2018), Labor market concentration does not explain the falling labor share, Technical report, Job Market Papers.
- Macaluso, Claudia, Brad Hershbein and Chen Yeh (2019), Concentration in US local labor markets: Evidence from vacancy and employment data, Technical report, Society for Economic Dynamics.
- Manning, Alan (2021), ‘Monopsony in labor markets: A review’, *ILR Review* **74**(1), 3–26.
- Manning, Alan and Barbara Petrongolo (2017), ‘How local are labor markets? evidence from a spatial job search model’, *American Economic Review* **107**(10), 2877–2907.
- Marinescu, Ioana, Ivan Ouss and Louis-Daniel Pape (2021), ‘Wages, hires, and labor market concentration’, *Journal of Economic Behavior and Organization* **184**, 506–605.

- Modestino, Alicia Sasser, Daniel Shoag and Joshua Ballance (2020), ‘Upskilling: Do employers demand greater skill when workers are plentiful?’, *Review of Economics and Statistics* **102**(4), 793–805.
- Oberfichtner, Michael and Martin Popp (2025 forthcoming), ‘Labor Market Concentration in Germany’, *German Economic Review* .
- Prager, Elena and Matt Schmitt (2021), ‘Employer consolidation and wages: Evidence from hospitals’, *American Economic Review* **111**(2), 397–427.
- Qiu, Y. and A. Sojourner (2023), ‘Labor-market concentration and labor compensation’, *ILR Review* **76**(3).
- Rinz, Kevin (2022), ‘Labor market concentration, earnings, and inequality’, *Journal of Human Resources* **57**(S), S251–S283.
- Robinson, Joan (1933), *The economics of imperfect competition*, Macmillan.
- Schubert, Gregor, Anna Stansbury and Bledi Taska (2023), Employer concentration and outside options, Technical report, Cato Institute.
URL: <http://www.jstor.org/stable/resrep51920>
- Tolbert, Charles M and Molly Sizer (1996), US commuting zones and labor market areas: A 1990 update, Technical report, United States Department of Agriculture, Economic Research Service.
- Traiberman, Sharon (2019), ‘Occupations and import competition: Evidence from denmark’, *American Economic Review* **57**(S), 4260–2301.
- Wachter, Till Von (2020), ‘The persistent effects of initial labor market conditions for young adults and their sources’, *Journal of Economic Perspectives* **34**(4), 168–194.
- Winter-Ebmer, Rudolf (1995), ‘Sex discrimination and competition in product and labour markets’, *Applied Economics* **27**(9), 849–857.