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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 able to explain employer power in setting pay and the work environment (Card, 2022). There are a large number of papers showing that monopsony leads to lower wages for workers (Rinz, 2022; Marinescu et al., 2021; Benmelech et al., 2022; Bassanini et al., 2021; Hirsch et al., 2018, 2022; Qiu and Sojourner, 2023). At the same time, studies from vacancy 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 policymakers 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 stems 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.

[2] These 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.

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

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

[5]See 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) provides an extensive discussion of this reform.

The AMS data show which person applied for a vacancy and which person actually got hired. This applies only to person 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.

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.

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

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

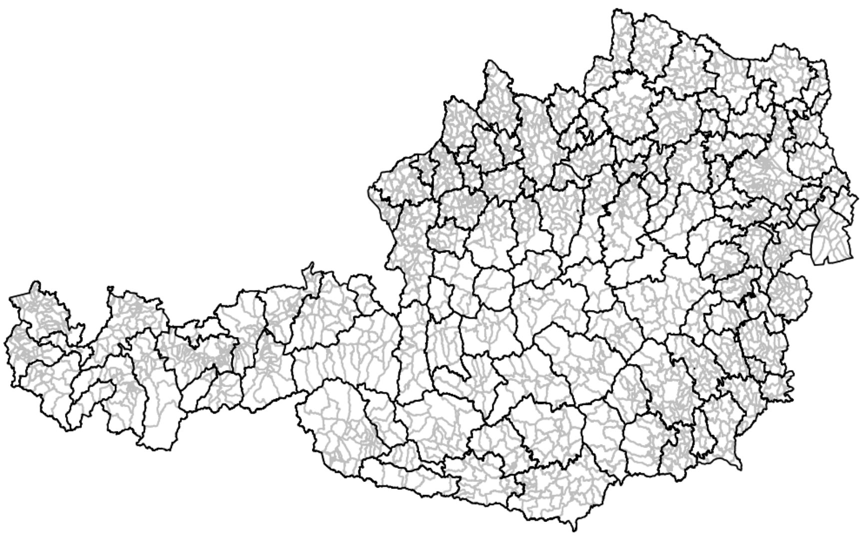
occupation. Therefore, we only keep occupation-commuting zone-year combinations when at least five vacancies are posted in a cell. This excludes thinly populated (rural) labor markets, where typical monopsony definitions would not work, i.e. a market with only one vacancy (from one firm) in a year leading 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 (2022) 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



[a]

[a]Notes: 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.

[7]Thanks to Karim Bekhtiar for providing us with these data (Bekhtiar, 2022).

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

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

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

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

Using job openings rather than employment to measure concentration has multiple advantages.[9] Job openings are likely a better measure of available work opportunities and firms' labor market power than employment. For instance, if labor market concentration influences the frequency with which workers vacate their jobs, basing our measure on employment may be less relevant than using job openings.[10] Wages of newly hired workers may also be more sensitive to conditions in the local labor market.

Almost all studies defined monopsony at an occupational and not an industrial level [11]; 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 index (HHI) (Berry et al., 2019).

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,

[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.

[9] Using 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).

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

[11] Exceptions 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

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 task*s (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 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. 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. 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. To exclude outliers, we drop the 5% lowest and 1% highest of daily wages in both actual and posted wages. Individual-level characteristics reveal a balanced and repre-

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

sentative 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	105150	.0019083	1	0.07	0.11
Gender	105150	0	1	0.53	0.50
Austrian	105150	0	1	0.92	0.28
Educational level	105150	1	5	2.23	1.06
Age	105150	22	66	38.87	10.10
Gross daily wage	105150	18.44	120.07	61.45	20.75
Posted daily wage	105150	11.05	205.48	52.35	10.55
Knowledge-based skills	103855	0	4	0.28	0.63
Soft skills	103855	0	3	0.91	0.94
Basic skills	103855	0	3	0.84	0.95
Benefits	103855	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.

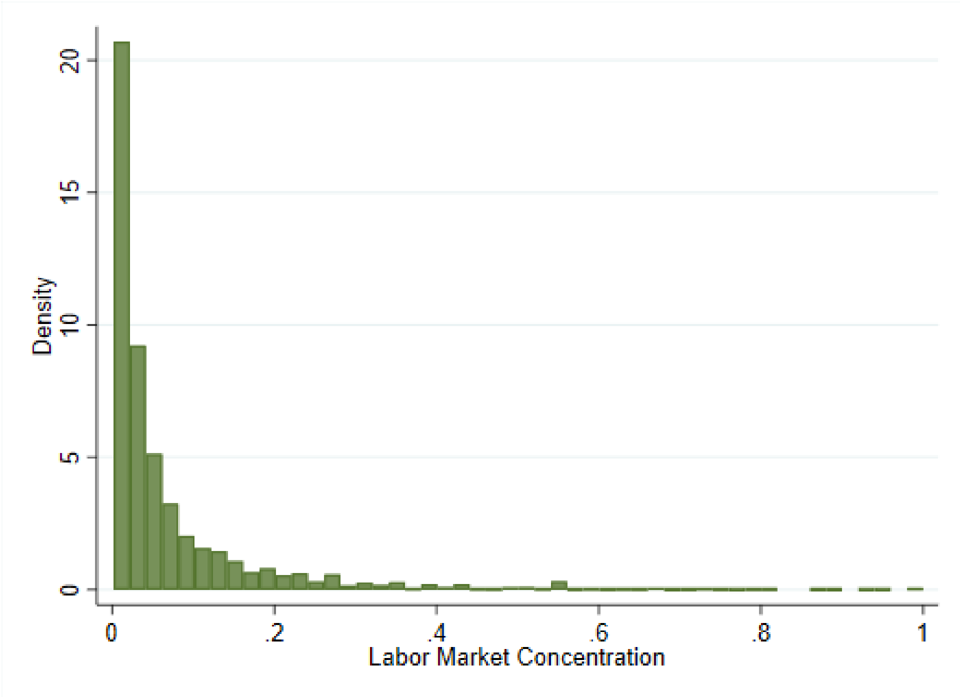
Using our matched vacancy-employer-employee data, our main specification is

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

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, age^2, 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

Figure 2: Distribution of labor market concentration



[a]

[a]Note: This figure depicts the distribution of the Herfindahl-Hirschman Index and was constructed using the AMS data.

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 workers can easily move between high-concentration local labor markets (commuting zones) and occupations, we would not expect to see an effect on wages. 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, and the semi-elasticity of non-wage amenities and skills when considering these other outcomes.

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)
Labor market concentration	-0.00781***	-0.01577***	-0.03236***	-0.03489***
	(0.00050)	(0.00093)	(0.00096)	(0.00188)
Age	0.00731***	0.00277***	0.00415***	0.00057
	(0.00040)	(0.00037)	(0.00077)	(0.00074)
Age^2	-0.00008***	-0.00003***	-0.00002**	0.00002**
	(0.00000)	(0.00000)	(0.00001)	(0.00001)
Gender	-0.04683***	-0.03895***	-0.22424***	-0.20067***
	(0.00125)	(0.00118)	(0.00242)	(0.00238)
Austrian	0.00819***	0.00154	0.00394	-0.00011
	(0.00170)	(0.00161)	(0.00328)	(0.00325)
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

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table presents the impact of 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.

[a]Mean 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 higher than in other countries.[13] To put our estimates into perspective, consider both a firm and a worker initially located in a local labor market and occupation at the 25th percentile of our concentration measure (0.012). Holding everything else constant, if these firm and worker experienced an increase in labor market concentration to the 75th percentile (0.08) the offered (posted) wages would be reduced by approximately 9% ($-0.0158 \cdot \frac{(0.08-0.012)}{0.012} \cdot 100 = -8.99\%$) while the actual wage the worker receives would decrease by 19% ($-0.0349 \cdot \frac{(0.08-0.012)}{0.012} \cdot 100 = -19.77\%$).

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 monopsony effect of actual wages and the monopsony effect of posted wages is the

[13]For example, the OLS estimates of Marinescu et al. (2021) for France imply an elasticity between -0.002 and -0.013, compared with an elasticity of -0.034 found for Austria.

impact of monopsony on on workers' bargaining power. The elasticity of bargaining power is -0.0191, 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 markets suffers more for young workers, women and Non-Austrians. This reverse effect for young workers may be due to there less experienced stance on the labor market.

Table 3: Labor market concentration and earnings by age group

	$log(Posted\ Wages)$ (≥ 37)	$log(Actual\ Wages)$ (≥ 37)	$log(Posted\ Wages)$ (< 37)	$log(Actual\ Wages)$ (< 37)
Labor market concentration	-0.02303***	-0.03871***	-0.01393***	-0.02991***
	(0.00250)	(0.00254)	(0.00272)	(0.00280)
Gender	-0.17092***	-0.21296***	-0.15749***	-0.19184***
	(0.00324)	(0.00330)	(0.00336)	(0.00347)
Austrian	-0.00112	0.00022	-0.00583	-0.00536
	(0.00397)	(0.00404)	(0.00530)	(0.00546)
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	0.207	0.423	0.222	0.425

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table presents the relationship between 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.

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.[14]

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 side, the impact of initial exposure to labor market concentration tends to fade over time. For example, the estimated coefficient 10 years after the initial exposure is roughly half the magnitude of the impact when initially hired. On the other side, recovery from initial exposure occurs only slowly, and even

[14]In 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

	$log(Posted\ Wages)$ Male	$log(Actual\ Wages)$ Male	$log(Posted\ Wages)$ Female	$log(Actual\ Wages)$ Female
Labor market concentration	-0.01546***	-0.02456***	-0.01525***	-0.03864***
	(0.00150)	(0.00232)	(0.00118)	(0.00293)
Age	0.00422***	0.01454***	0.00146***	-0.01327***
	(0.00055)	(0.00086)	(0.00048)	(0.00120)
Age^2	-0.00004***	-0.00016***	-0.00002***	0.00019***
	(0.00001)	(0.00001)	(0.00001)	(0.00002)
Austrian	0.00440*	0.00840**	-0.00029	-0.01269**
	(0.00238)	(0.00368)	(0.00214)	(0.00531)
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

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table examines the relationship between 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.

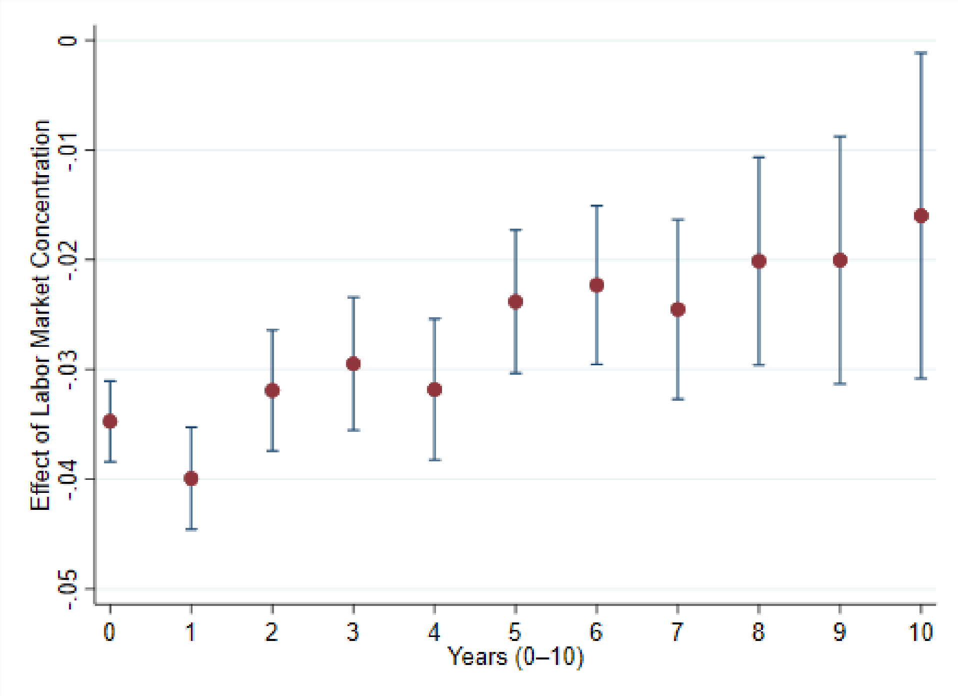
Table 5: Labor market concentration and earnings by nationality

	$log(Posted\ Wages)$ Austrians	$log(Actual\ Wages)$ Austrians	$log(Posted\ Wages)$ Non-Austrians	$log(Actual\ Wages)$ Non-Austrians
Labor market concentration	-0.01609***	-0.03412***	-0.01291***	-0.03939***
	(0.00098)	(0.00197)	(0.00306)	(0.00669)
Age	0.00310***	0.00049	-0.00049	-0.00023
	(0.00039)	(0.00078)	(0.00115)	(0.00253)
Age^2	-0.00003***	0.00002**	0.00001	0.00002
	(0.00000)	(0.00001)	(0.00001)	(0.00003)
Gender	-0.03959***	-0.20356***	-0.03056***	-0.16654***
	(0.00125)	(0.00251)	(0.00350)	(0.00766)
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

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table examines the relationship between 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.

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



[a]

[a]Note: This graph depicts the impact of the Herfindahl-Hirschman Index (log(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 a 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.[15]

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

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

monopsonistic labor markets are less likely to offer non-monetary amenities and fewer amenities overall. Both estimates are statistically significant and of considerable magnitude. To illustrate our estimates, an increase in the HHI index from the 25th to the 75th percentile reduces the probability of a firm offering non-monetary benefits by nearly 10 percentage points.[16] Similarly, the number of amenities provided by firms decreases by 0.10. Together with our estimates for wages, the results imply on one side 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) Any benefits offered	(2) Number of benefits offered
Labor market concentration	-0.05113***	-0.05710***
	(0.00308)	(0.00480)
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	0.1641	0.1420

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table shows the effect of labor market concentration measured as log(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.

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 opportunities for skill development.[17] The results are presented in Table 7.

Our estimation results are presented in Table 7. Columns (1) to (3) report the impact of

[16] This is calculated as $\log(\frac{0.08}{0.012}) \cdot -0.0513$.
[17] Arellano-Bover (2024) does not investigate the role of monopsonistic labor markets in his study.

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
Labor market concentration	0.00228	0.00408	0.01642***	-0.00210	-0.00078	0.02577***
	(0.00218)	(0.00302)	(0.00296)	(0.00332)	(0.00556)	(0.00555)
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	0.3641	0.1927	0.2409	0.4031	0.2497	0.2672
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

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

Notes: This table examines the effect of 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.

We do not find evidence for the upskilling theory, neither for the likelihood of requiring any knowledge-based or soft skills - see Columns (1) and (2), nor for the number of such skills required - see Columns (4) and (5).[18] 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). 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. While we cannot directly investigate whether higher demand for basic and ultimately lower-productivity skills drives our long-run 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 (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.

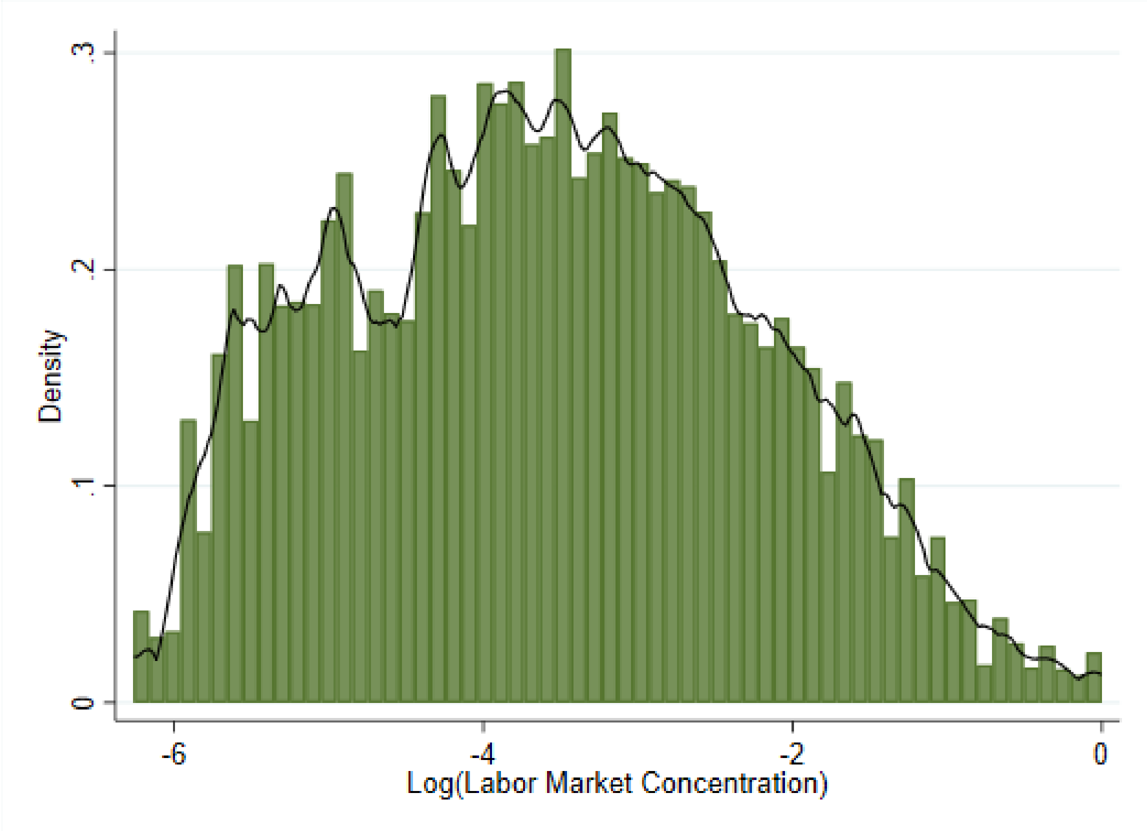
[18] Related to these results Macaluso et al. (2019) and Qiu and Sojourner (2023) find that firms in monopsonistic markets are not able to hire higher-skilled workers at lower wages.

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



[a]

[a]Notes: 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)
	$log(Actual\ Wages)_1$	$log(Actual\ Wages)_2$	$log(Actual\ Wages)_3$	$log(Actual\ Wages)_4$	$log(Actual\ Wages)_5$
Labor market concentration	-0.040***	-0.032***	-0.029***	-0.032***	-0.024***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Age	0.004***	0.010***	0.019***	0.028***	0.037***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender	-0.239***	-0.232***	-0.236***	-0.240***	-0.253***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Austrian	-0.001	0.005	0.009	0.014**	0.018***
	(0.004)	(0.005)	(0.005)	(0.006)	(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

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 $log(Actual\ Wages)$, with Columns (1) through (5) showing wages from year 1 to year 5. The independent variable, $Labormarketconcentration$ 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.

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

	(1) $log(Actual\ Wages)_6$	(2) $log(Actual\ Wages)_7$	(3) $log(Actual\ Wages)_8$	(4) $log(Actual\ Wages)_9$	(5) $log(Actual\ Wages)_{10}$
Labor market concentration	-0.022***	-0.025***	-0.020***	-0.020***	-0.016**
	(0.004)	(0.004)	(0.005)	(0.006)	(0.008)
Age	0.045***	0.046***	0.049***	0.052***	0.050***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender	-0.254***	-0.245***	-0.240***	-0.262***	-0.294***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.009)
Austrian	0.025***	0.019***	0.020**	0.029***	0.027**
	(0.006)	(0.007)	(0.008)	(0.010)	(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

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 *labormarketconcentration* 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.

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