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Making their own weather? Estimating employer labour-market power and its wage effects[☆]

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ABSTRACT

The subdued wage growth observed in many countries has spurred interest in monopsony views of regional labour markets. This study measures the extent and robustness of employer power and its wage implications exploiting comprehensive matched employer–employee data. We find average (employment-weighted) Herfindhal indices of 800 to 1,100, stable over the 1986–2019 period covered, and that typically less than 8% of workers are exposed to concentration levels thought to raise market power concerns. When controlling for both worker and firm heterogeneity and instrumenting for concentration, we find that wages are negatively affected by employer concentration, with elasticities of around −1.4%. We also find that several methodological choices can change significantly both the measurement of concentration and its wage effects.

1. Introduction

The limited wage growth observed in many countries in the recovery following the 2008 financial crisis and during the recent inflationary period since 2021 has prompted important questions about the degree of wage setting power enjoyed by employers. These questions have received additional attention following the recent evidence of declining labour shares, the rise of 'superstar firms' (Autor et al., 2020), the relevance of 'non-compete' and 'no-poaching' arrangements (Krueger and Ashenfelter, 2022), and the limited disemployment effects of minimum wages. While many of these findings may still be reconciled with largely competitive labour markets, the relevance of evidence on the extent of employer labour-market power and its effects is clear. For instance, competition agencies may need to pay more attention to labour markets — while labour policy may also need to pay more attention to competition issues.

This paper contributes to the literature on labour monopsony (Staiger et al., 2010; Manning, 2010, 2011; Falch, 2010; Matsudaira, 2014; Webber, 2015; Card et al., 2018) by providing empirical evidence on two major questions: first, how concentrated are local labour markets? and, second, what is the impact of labour market concentration on wages? Together with Rinz (2022), we believe we are among the first in this growing literature to address these questions by exploiting rich matched employer–employee data: our data covers the full population of workers (and occupations) in a European country, Portugal. Furthermore, we exploit the availability in our data of information on the occupation, industry, region, and wages of each worker. For instance, in contrast to some other papers, we consider not only manufacturing but also services. All variables are particularly detailed and comparable not only across firms but also over time, during the very long (34-year) period that we cover.[2]

Two of the data dimensions above – coverage of both all occupations and of the entire labour market – are critical for a comprehensive analysis of employer market power. The majority of workers in developed countries have been for many decades employed in the services sector (which is however not covered in a number of data sets used

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2 To our knowledge, only Rinz (2022) and Benmelech et al. (2022) analyse such long periods.

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in this research) and concentration levels may be very different (much higher) in manufacturing than services. Moreover, less than comprehensive information of the location of comparable occupations across firms and regions as well as an analysis based exclusively either on employment flows or stocks may also lead to overestimated measures of concentration.

A key reference in this literature is Azar et al. (2022) (see also Azar et al. (2020)): using data on the top occupations from a leading U.S. employment website, they find that the average labour market is highly concentrated. Moreover, using a subset of their data for which posted wage information is available, they find that concentration is associated with large declines in earnings, of 17% from moving from the 25th to the 75th percentile of the Herfindhal distribution. Additional important contributions include Benmelech et al. (2022) and Rinz (2022) on the U.S, Dube et al. (2020) on online markets, Bassanini et al. (2023a) on six European countries (including Portugal),[3] Dodini et al. (2023) and Dodini et al. (2021) for Norway, Bassanini et al. (2023b) and Marinescu et al. (2021) on France, and Duan and Martins (2022) on China, the latter two also considering the role of rent sharing. Because of data limitations, some of these papers only examine manufacturing or cannot consider the roles of occupations or of employment stocks.

Our results are consistent with the previous literature in that we also find that employer market power is a significant phenomenon in both its magnitude and time constancy. However, our results indicate that employer market power potential, as measured by concentration indices,[4] is smaller than in earlier evidence that could not draw on data with the same level of detail. This finding of smaller employer market power applies both in terms of the percentage of the workforce employed in high-concentration local labour markets and in the size of the wage effects of concentration. Specifically, we find that less than 9% of workers are exposed to concentration levels thought to raise (product) market power concerns (DoJ/FTC, 2010).

One of our contributions is the finding that methodological choices can have a significant impact on the levels of labour market concentration and the magnitude of its wage effects. Leveraging our comprehensive data, which encompasses variables not concurrently available in datasets used in other studies, we are able to explore a variety of methodological choices. As a result, this paper provides a benchmark for comparing findings from research that adopts only specific methodologies.

We find that defining job characteristics using workers' industry – such as Rinz (2022) – rather than occupation – such as Azar et al. (2022) – and deciding the degree of occupational specificity can significantly impact both the measured levels of concentration and its wages effects. For instance, using industry-based definitions of local labour markets can lead to twice as high wage markdowns than occupation-based ones. We also find that labour-market concentration can more than double when considering more granular occupation codes. Altogether, our results highlight the considerable quantitative (even if not qualitative) sensitivity of estimates to methodological choices.

Another contribution is to better understanding the importance of worker and firm time-invariant heterogeneity when estimating wage effects of labour-market concentration. This is in contrast to research which, due to data limitations, does not control for these factors. When not controlling for both worker and firm fixed effects, we find a positive association between employer concentration and wages. This may reflect the fact that concentrated labour markets tend to be characterised by large firms, which can be more productive and or enjoy stronger product market power. These two dimensions will in turn create scope both for stronger selection in hires (recruiting and retaining workers of higher productivity) as well as rent sharing, through bilateral bargaining. The latter can apply particularly when labour market policies are supportive of collective bargaining and unionisation, as is the case of Portugal and much of continental Europe. On the other hand, some of these countries are characterised by strong employers' associations (Martins, 2020), which can facilitate collusion in wage setting across firms in the same industry (Martins and Thomas, 2023).

We assess the potential relevance of these multiple factors by again exploiting the richness of our data and estimating the relationship between wages and concentration while controlling both for worker and firm fixed effects. We follow Azar et al. (2022) and employ instrumental variables based on the number of firms in the same occupations but other local labour markets. In these models, we find a negative effect of local labour market concentration on wages, with elasticities of −1.4%. These results indicate that workers that would move from low- to high-concentration local labour markets (percentiles 25th and 75th, respectively) would experience a drop in wages of approximately 3.5%, a figure significantly smaller than in Azar et al. (2022). Interestingly, the effect of concentration does not appear to be fully linear: elasticities increase when moving from the first to the third quartiles of the concentration distribution but decrease at the fourth quartile.

Our paper also contributes to the literature examining the role of labour market institutions in counteracting monopsony power (Benmelech et al., 2022; Bassanini et al., 2023a; Dodini et al., 2021). Indeed, the smaller effect that we find, when compared to studies using U.S. data, may reflect institutional differences. For instance, sectoral collective bargaining is much stronger in Continental Europe than the U.S., and may weaken the negative effect of employer market power on wages. To test for this, we interact labour-market concentration with a measure of collective bargaining coverage (including sectoral or other agreements). As Bassanini et al. (2023a), we find evidence that higher coverage rates by collective bargaining agreements attenuate wage markdowns.

Finally, our findings shed new light on the role of larger firms in concentrated labour-markets. One paper that takes firm size into account is Rinz (2022), who suggests that top employers may be important drivers of labour market-concentration. An asymmetric Cournot model (Boal and Ransom, 1997) also predicts that, in more concentrated markets, large firms are able to impose stronger wage markdowns than smaller employers. Here, we examine whether, for any given level of concentration, larger firms impose stronger wage markdowns and, indeed, we find that top-five local employers exhibit larger wage effects than smaller firms. This result also suggests an important role for search-friction based explanations of monopsony.

The structure of the remaining of the paper is as follows: Section 2 presents the matched employer–employee data used. Section 3 describes our main measures of employer concentration and a comprehensive sensitivity analysis. The wage effects results and their robustness as well as some extensions are presented in Section 4. Section 5 concludes.

2. Data

Our study is based on the 'Quadros de Pessoal' (Personnel Records) data set, a comprehensive matched employer–employee panel. This data set provides detailed annual information on all firms based in Portugal that employ at least one worker, including information on each of their employees, their establishments, and time-invariant firm, establishment, and worker identifiers. The data set follows from an annual mandatory survey collected by the Ministry of Employment for the purposes of enforcing compliance with employment law and collective bargaining.

Worker individual information concerns the month of October of each year (March up to 1993) and features a number of variables, the most important for us being the monthly wage (base and total) and the occupation. The latter is defined using the national occupations

[3] We note that Bassanini et al. (2023a) use a different period in their analysis of Portugal (2010–2019).

[4] There are other measures that also measure market power, including the elasticity of labour supply to the firm (Manning, 2021).

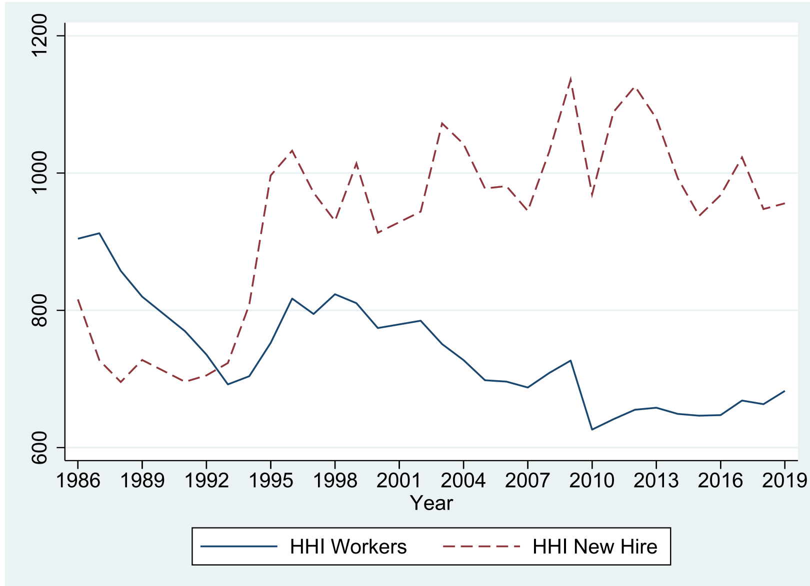

Fig. 1. HHI by number of employees and of new hires (weighted), 1986–2019. **Notes:** Own calculations based on the 'Quadros de Pessoal' data set. See the Herfindhal index formula in Eq. (1) and Table A.1 for more details on each time series. Figures for 1990 and 2001 are interpolated as worker-level data for these years are not available. Occupation codes change in 1995 and 2010. The weights of the two series are the employment count of each occupation–district–year cell. 'HHI works' corresponds to employment stocks; 'HHI new hires' corresponds to employment flows (workers employed in October of each year (March, up to 1993) and hired over the previous 12 months).

classification, which features about 1400 different entries, defined at a six-digit level in most of the period. Other worker-level variables that we also consider include the year and month of hiring by the firm, the applicable collective agreement, and the job title code of the worker under the collective agreement. At the establishment level, we use its geographical location (at the 'concelho' level – over 300 different locations – and the more aggregated 'distrito' level — 30 different locations).[5]

Our benchmark definition of local labour markets is based on the occupation definition composed of 1400 different values and the region definition composed of 30 'distritos' (including islands). These regions have an average size of about 3000 square kilometres and 340,000 inhabitants, including multiple cities and villages in most cases. 18 regions are located in the continental part of Portugal; the remaining 12 correspond to the islands of Azores and Madeira. With the exception of some areas in the least populated and least densely populated regions, typically located in the East and South of the country, all urban or industrial areas can be reached from virtually all residential areas in each district in less than one hour by car or public transport. With the exception of the district of the capital city, Lisbon, the largest city in each region is located closed to the geographical centre of the region. This ensures limited overlap between commuting zones of neighbouring regions. This benchmark definition also leads to an average of 14,300 local labour markets (occupation–region pairs) per year over the 33-year period covered, as we discuss below. We also consider all years between 1985 and 2019 (except 1990 and 2001, which are not available in the data).

[5] We use all worker observations in the data set except the small number with missing information on the occupation, date of hiring, and region variables. At the establishment-level, the data also provides information on industry (five-digit variable) - see Cahuc et al. (2023) for a recent analysis of the establishment dimension of this data. At the firm-level, available information includes total sales, legal type of firm, capital equity, and type of ownership.

3. Employer concentration

Following the literature, we measure employer concentration using the Herfindhal–Hirschman index (HHI):

$$HHI_{l(o,d),t} = \sum_{j=1}^{N(l,t)} share_{j,t}^2, \tag{1}$$

in which $HHI_{l(o,d),t}$ is the HHI measure for local labour market l (correspond to both occupation o and district d), in year t; $N(l,t)$ is the number of firms employing (or having hired) workers in that occupation, district and year; and $share_j$ is 100 times the ratio between the employment (or new hires) of firm i in year t and the total employment (or new hires) in the local labour market of that firm (occupation o and district t in year t). Given this definition, the HHI can range between 0 — no concentration — and 10,000 — maximum concentration (a single firm).

In Fig. 1, we present the HHI indices for each year, considering the cases of employment ('stocks') and new hires ('flows'). Moreover, in Table A.1, we also present these indices for both weighted and unweighted measures. 'Flows' are defined as workers employed in the firm as of the census month – October of each year since 1994 (March of each year until 1993) – and hired over the previous 12 months.[6] The results indicate that the mean annual (weighted) HHIs in the case of stocks range between 625 and 912, while in the case of flows they range between 700 and 1167. These figures are significantly below the concentration levels thought to raise market power concerns, at least in the case of product markets, at HHIs of 2500.[7] We acknowledge

[6] Note that we do not observe very short spells corresponding to new hires over the eleven months before the census month whose employment comes to an end before such census month.

[7] Fig. A.1 presents an illustration of this approach, considering one particular occupation, construction and public works technician (code 31120), in a particular district (Leiria), and in a particular year (2006). Each observation in the histogram corresponds to one of 240 firms, located in the district, that employ at least one worker of this occupation in that year. The Herfindhal index for this case is 51.7, highlighting the significantly dispersed nature of the employment of this occupation in this district, as over 200 of the 240 firms employ only one worker registered in this occupation.

Table 1
Descriptive statistics, district–occupation–year cells, 1985–2019.

Variable	Obs	Unweighted		Weighted		Min	Max
		Mean	Std. Dev.	Mean	Std. Dev.		
Year	470,782	2003.1	9.2	2004.5	9.5	1985	2019
Number of workers	470,782	174.2	1063.4	6665.6	13 490.7	1	105 322
Number of new hires	470,782	35.0	250.3	1419.6	2747.3	0	18 044
HHI (n. of workers)	470,782	4262.5	3720.1	725.9	1666.6	1	10 000.0
HHI (n. of new hires)	470,782	3201.2	3846.6	997.9	1914.1	0	10 000.0
Mean base pay	463,996	601.8	595.3	561.6	597.0	0	39 452.2
Mean total pay	463,996	706.0	709.6	646.4	685.5	0	39 452.2
Mean Col. Barg. coverage	470,782	0.81	0.39	0.82	0.38	0	1

Notes: Each observation corresponds to a district–occupation combination observed in a year. 'Unweighted' ('Weighted') denotes statistics in which all cells carry the same weight (each cell carries the weight proportional to its employment). 'Mean base pay' is the average nominal base pay of the workers employed in the district–occupation–year cell. 'HHI (n. of workers)' denotes the Herfindhal index (under its stock-base measure) for each district–occupation–year cell. 'HHI (n. of new hires)' denotes the Herfindhal index (under its flow-base measure) for each district–occupation–year cell. 'Mean Col. Barg. coverage' is the average coverage of workers by any type of collective bargaining agreement for each district–occupation–year cell.

that the relevance of this threshold is debatable in the context of labour markets, which have different dynamics from those of product markets.[8] Nonetheless, for comparative purposes with prior literature, we use it as a reference.

Fig. 1 also indicates that there is no particular trend in concentration. Specifically, there is no clear evidence of an increase in labour market concentration over time. If anything, we find a possible downward trend, particularly over the period 1998–2010, in the stocks measure. The data may also be consistent with moderate counter-cyclicality, particularly in the hires measure: years such as 2004, 2009 and 2012, when unemployment increased significantly, are also periods of above-average HHIs. These high HHIs will reflect not only the steep reductions in hires during downturns but also the particular distribution of hires across firms that arises then, in such a way that the HHI concentration measure increases significantly.

How do the stock and flow series compare? Table A.1 indicates that the HHIs in stocks are almost always lower than the corresponding (same year) HHI's in flows. For instance, in 2006, the former is 696 and the latter 981. Overall, flows HHIs are, on average, about 30% higher than stocks HHIs. This gap reflects the fact that not all firms employing workers in a given year also hire in that same year. On the other hand, Table A.1 indicates that unweighted measures lead to much higher measures of concentration.

Table A.1 also presents information about the number of occupation–district cells used to compute the HHIs as well as the total number of workers and new hires in each year. The first series ranges between 11,000 and 21,000 cells, reflecting the growth of the formal sector since the late 1980s and a change in occupation codes in 1995 and in 2010, as well as the labour effects of the financial crisis and debt crises from 2008. The numbers of workers and new hires follow a similar pattern to that of local labour market cells, increasing from 1.6 million employees (200,000 new hires) to 3.2 million employees (808,000 new hires), over the period.

We also describe our data in terms of the nearly 470,000 local labour market cells considered, when pooling over the entire period of our analysis, 1985–2019 - Table 1. The mean number of workers per cell is 174, while the mean number of new hires is 35 (both statistics are not weighted). The mean HHI measures are, when considering employment stocks, 726 (weighted) and 4263 (unweighted). When considering employment flows (new hires), these figures are 998 and 3201, respectively. The latter figure is the most comparable with those reported in Azar et al. (2022), based on 16 of the most frequent occupations posted on a large online jobs board in the US over 2010–2013, which present a remarkably similar mean HHI figure of 3157. While Azar et al. (2022) focus their analysis on average HHIs across local labour markets, we focus on employment-weighted HHIs, i.e. we adopt the perspective of the labour market faced by the average worker (and not that of the average labour market), to take into account the possibility – supported in our analysis – that concentrated labour markets tend to be characterised by small numbers of workers. We also find an interquartile range of 510 HHI points (556 - 46) when weighting cells by employment but much higher, 7216 (8144 - 928), when not weighting.[9]

To illustrate our findings, Fig. 2 presents the distributions of HHIs across local labour markets (district–occupation pairs) in a particular year, 2006, not weighting or weighting each cell by its employment (left- and right-hand-side histograms, respectively), considering stocks or flows (top and bottom graphs, respectively). As in the case of the pooled cells, we find that this weighting makes a significant difference, as the most concentrated local labour markets tend to be those employing fewer workers, in many cases a single worker. Very similar results emerge when considering different years than 2006. The range of HHI concentration levels between 0 and 2000 is the one that applies to most workers, as in the case study of a particular occupation (construction/public works technician) in a particular district (Leiria) presented above and in Fig. A.1.[10]

[8] As Azar et al. (2022) note, the two-sided matching process between buyers (firms) and sellers (workers) may render labour markets less active compared to one-sided product markets. Thus, any given level of concentration may affect these markets differently.

[9] See Table A.2. Standard deviations of HHI measures range between around 1600 (weighted analysis) and 3800 (unweighted case), regardless of the type of measure (stock or flow). Furthermore, mean salaries range between 561 and 706 euros, depending on whether one is considering base or total wages and weighted or unweighted means. We consider these figures later, when computing the wage implications of more concentrated markets, together with the elasticities presented in Section 4.

[10] To provide greater detail on our results, we also describe here a subset of occupations with the highest and lowest HHI values. Focusing, as an illustration, on those occupations employing at least 1000 workers in a particular year, 2006, the occupations that are associated to the lowest levels of concentration are 'Director and managers of small firms' (13 110–13 199 occupation codes; average HHI of about 40), 'Production director' (12 220; 33), and 'Secretary' (41 150; 34). These cases reflect the fact that almost all firms employ only one or at least one worker in such occupations. On the other hand, the occupations with the highest levels of concentration are 'Postman' (41 420; 9904), 'Train driver' (83 110; 9880), and 'Industrial robot operator' (81 729; 9708). The first two cases reflect the fact that the post distribution and train transport industries operate as (product market) monopolies in Portugal, as in many other countries.

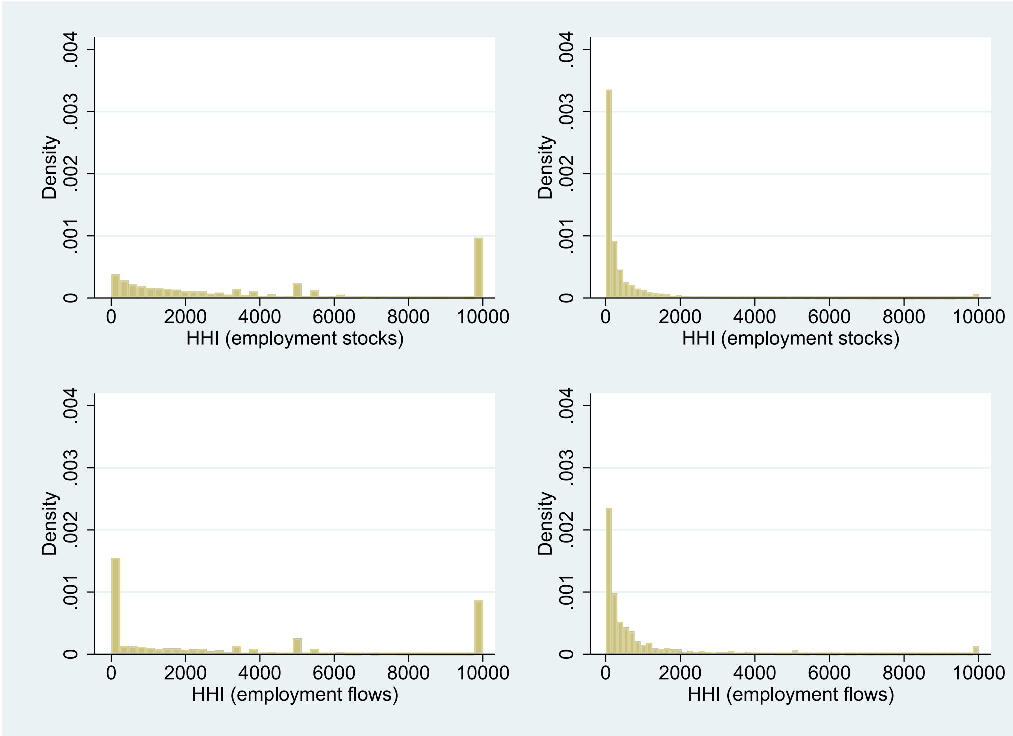

Fig. 2. Distribution of HHI by number of employees across local labour markets (left: unweighted; right: employment-weighted; top: stocks; bottom: flows), 2006. **Notes:** Own calculations based on the 'Quadros de Pessoal' data set. See the Herfindhal formula in Eq. (1). Left-hand-side distributions: All local labour markets (occupation–district pairs) carry the same weight, regardless of the number of workers. Right-hand-side distributions: Each local labour markets (occupation–district pairs) carries a weight in the histogram that is proportional to its employment level. Top (bottom): measures based on employment stocks (flows).

3.1. Sensitivity

The results above follow from specific choices regarding the definition of a local labour market. Before presenting the effects of labour-market concentration on wages, we investigate the robustness of our findings to different definitions. Departing from our benchmark model above (based on 1400 occupations and 30 districts), we exploit the richness of our data to measure local labour markets in up to seven alternative ways, to better understand the sensitivity of labour-market concentration measures.

In the first alternative approach, we consider a narrower classification of occupations: collective bargaining job titles. There are typically over 30,000 job titles established in collective agreements in any one year, each one typically subject to a different and time-varying minimum wage, and in total covering nearly the full employee population (Martins, 2021). However, these alternative occupation measures are also very likely to double-count the same occupations and thus overestimate the number of local labour markets, leading to spuriously high concentration levels.[11] Table 2, second row, presents the results (the first row presents the benchmark results, weighted by employment, to facilitate the comparison with alternative measurement approaches). This definition of occupations leads to a significant increase in the average number of labour-market cells, from 14,266 to 81,539, as occupation codes increase by more than a factor of 20 when moving from the benchmark case to collective bargaining job titles. We find that average HHI measures more than double in both cases (employment stocks and flows), reaching 1785 and 2033, respectively. The percentage of workers in local labour markets with HHIs above the 2500 also more than doubles, reaching nearly 20%, a figure considerably above the benchmark case (7.5%) and more in line to the one found for the U.S. in Azar et al. (2020).

A second approach is to consider occupations at a more aggregated level. Consistent with our results using collective bargaining job titles, when we define labour markets using a 4-digit classification instead of a 5-digit one, we observe lower levels of labour-market concentration under both measures of HHI.

A third alternative measure involves considering more disaggregated regional definitions ('concelhos' instead of 'districts'). This option is influenced by the findings in Manning and Petrongolo (2017), which present evidence that labour markets can be very local, as jobseekers reduce their search efforts considerably at longer commuting distances. In our case, the 'concelho' level has 10 times more units in total when compared to 'distritos' and are roughly equivalent to U.S. counties.[12] We find, first, that the number of occupation–region–year cells increases by more than four times from the benchmark case to over 60,000, reflecting the far more disaggregated nature of the local labour market - Table 2, fourth row. On the other hand, the HHI measurements also increase, to 1461 and 1908, for employment stocks and flows, respectively. While this change is significant, these averages fall short of the levels measured in the case of collective bargaining titles and also correspond to a smaller percentage of workers in local labour markets above the critical thresholds of 2500 (17.8% in this case).

[11] For instance, a secretary in the metalwork industry will have a different collective bargaining job title code than a secretary in the retail sector even if their jobs are highly substitutable and if both employees are located in the same district. Future research may consider instead the description of the job title to match occupations across industries.

[12] As this level will be too small to be considered a distinctive commuting zone in the cases of the two largest metropolitan areas, Lisbon and Porto, which are served by good public transport links, we still consider units based on 'distritos' (not 'concelhos') in those two particular cases.

Table 2
HHI mean values, different measurement approaches.

Measurement type	HHI		Average number of			% workers
	Workers	Hirings	cells	workers	hirings	HHI ≥ 2500
Benchmark case	742.8	943.7	14 266	2 485 313	499 541	7.5
Collective barg job titles	1784.9	2032.8	81 539	2 485 313	499 541	19.7
Occupation (agg at 4 digits)	513.6	670.0	6948	2 485 313	499 541	4.7
Less aggregated regions	1460.8	1907.5	61 094	2 485 313	499 541	17.8
Hirings (prev 6 months only)		996.8	14 266	2 485 313	435 746	11.5
Hirings (from a different firm)		1022.4	14 472	2 549 341	295 118	12.2
Only firms without public equity	613.4	907.9	13 633	2 333 790	490 198	6.0
Only firms 10+ employees	1017.9	1334.1	12 682	1 880 514	366 342	10.7
Manufacturing sector only	1137.3	1815.0	8218	694 827	90 138	13.5
Industry	1667.5	1515.1	9628	2 485 313	499 541	18.8

Notes: 'Benchmark' measurement type is the main one adopted in the paper, based on approximately 1400 occupations and 30 districts. 'Collective bargaining titles' is the same approach as the benchmark model except that, instead of considering occupations, we differentiate occupations by using the collective bargaining job titles (about 30,000). 'Occupation (agg at 4 digits)' is the same approach as the benchmark model except that, instead of considering 5-digit occupations, we use the 4-digit classification. 'Smaller districts' is the same approach as the benchmark model except that, instead of considering the 30 district codes above, we consider instead a finer classification, amounting to 452 different codes. 'Hires in previous 6 months' is the same approach except that the HHI in flows measure is based on workers hired over the previous six months only (and not the previous 12 months, as in the benchmark and all other measurement approaches). 'Hires (from a different firm)' is the same approach except that the HHI in flows measure is based on new hires that worked for a different firm in the previous year. 'Only firms without public equity' is the same approach as the benchmark model except that we disregard from the analysis firms that have some level of public equity. 'Only firms 10+ employees' is the same approach as the benchmark model except that we disregard from the analysis firms that, in each year of the analysis, employ with fewer than 10 employees. 'Manufacturing sector only' is based on manufacturing firms only. 'Industry' defines labour-markets using the 5-digit industry classification rather than occupation. HHI and number of cells, workers and hires are unweighted averages of the weighted HHI yearly data, over the 1986–2019 period. The last column indicates the weighted percentage of cells across all years that have HHI levels above 2500 (workers HHI except the second row, which denotes new hires HHI).

Another alternative from our benchmark measure is based on restricting the time window under which a worker is considered a new hire, from the 12-month period used before to six months only. Our interest in this analysis stems from the vacancy perspective (Azar et al., 2022, 2020). We find that the HHI for new hires increases by only 6%, from 944 to 997 (the employment stocks results are unchanged as they are not affected by this criterion). The number of new hires is naturally reduced, from about 500,000 to 435,000, as in some local labour market hires only take place in the first half of the year. Overall, despite halving the time window adopted for the consideration of new hires, the degree of concentration increases by a much smaller magnitude, indicating that these measures are not very sensitive in this dimension.

An additional perspective is to consider only job-to-job mobility when calculating labour market concentration. Job-to-job mobility may involve poaching and thus may be a better measure for concentration purposes, as it is more focused on the demand side. General hires (including those from non-employment) may be influenced considerably by supply factors (e.g., new graduates or immigrants entering the labour market) that may dampen concentration levels. Drawing on the longitudinal nature of the data, we proxy job mobility by focusing on new hires employed in a different firm in the previous year. (We also exclude 1985, 1991, and 2002, as there is no employee data for the years before.) We find that HHI (flows) increases by 8% to 1022.

Another approach follows from the fact that public-sector firms tend to operate as monopolies and employ a large share of all workers in specific occupations. Examples of the latter are postman and air traffic controller. (However, given their public-sector affiliation, these firms may not use their labour market power in the same way that a private-sector firm in a similar position, an idea that we will test later.) To understand if public-sector firms affect our benchmark measure of concentration, we exclude firms with any positive level of public ownership of their capital equity. This new sample yields a decrease in HHI, from 744 to 613 (stocks) or from 944 to 908 (flows).

We also examine the role of the large percentage of small firms in the labour market of Portugal as a potential driver of the low HHI levels found so far.[13] Removing firms with fewer than 10 employees from our analysis leads to a significant decrease in the average number of workers and hires, and a corresponding increase in HHI measurements. However, this increase is not as high as in other measurement approaches. Hence, our findings suggest that firm size is not the main factor behind the low concentration measures found in our benchmark analysis.

Finally, we consider the sector dimension. As indicated before, some studies of employer concentration define local labour-markets using the firm's industry rather than the worker's occupations or only examine the manufacturing sector because of data limitations (Benmelech et al., 2022; Duan and Martins, 2022; Rinz, 2022). In order to shed light on the potential impact of such methodological approaches, we focus on the industry of each establishment indicated in our data to make two additional analyses. First, we restrict our attention to manufacturing sector establishments only. Row seven of Table 2 presents the results, which indicate significantly higher levels of concentration, with stock and flows HHI's of 1137 and 1815, respectively, and an employment share above 2500 of 13.5%. Second, we define local labour-markets as industry-by-region cells, using 5-digit industry classifications. Here we find that the HHI stock measure increases by 125% compared to the benchmark case, while the flows measure increases by 60%. Under this case, about 19% of workers are exposed to a level of concentration greater than 2500.

In conclusion, by exploiting the richness of our data, we find that the measurement of employer concentration is sensitive to different methodological choices. Specifically, most – but not all – departures from our benchmark case increase concentration estimates. In any case, the direction and magnitude of the variation of our estimates across methods may be particularly useful when considering findings from studies that draw on less comprehensive data. In our next section, we complement this analysis by presenting evidence on the implications of some of these alternative measurements on the magnitude of the wage effects of concentration.

[13] As documented in Cabral and Mata (2003) and Braguinsky et al. (2011), Portugal tends to exhibit a larger mass of smaller firm sizes than other countries. This may be due to limited access to credit, strict employment laws, and a over-reliance on service providers over formal employees.

Table 3
Wage results, OLS, 1986–2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Log Herfindhal Index (Stocks)	0.018		−0.002		−0.005	
	(0.002)***		(0.001)*		(0.001)***	
Log Herfindhal Index (Flows)		−0.001		−0.004		−0.002
		(0.002)		(0.001)***		(0.000)***
N	69 348 046	68 191 301	69 348 046	68 191 301	69 348 046	68 191 301
adj. R^2	0.588	0.585	0.785	0.783	0.818	0.817
F	55.93	.1045	3.179	13.99	53.45	23.35
(District x Year) FEs	1	1	1	1	1	1
(Occupation x District) FEs	1	1	1	1	1	1
Firm FEs	0	0	0	0	1	1
Worker FEs	0	0	1	1	1	1

Notes: The columns present different specifications of wage equation (2). The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above – see Table 1 – based on either employment stocks (odd columns) or flows (even columns). '(District x Year) FEs' denote fixed effect for each district–year pair. '(Occupation x District) FEs' denote fixed effect for each district–occupation pair. '1' denotes that the set of instruments in the row is included in the specification. Standard errors clustering at the local labour market level. Significance levels: * 0.10, ** 0.05, *** 0.01.

4. Wage effects

If workers have limited choice in alternative employers in their occupation and commuting zone, firms may exploit the resulting wage setting power by reducing the pay offered to, and eventually accepted by workers. In this context, after establishing above the levels (and sensitivity) of employer concentration across labour markets and time periods, we now estimate the impact of such concentration on wages. Specifically, in our benchmark specifications, we consider the following equation:

$$logY_{i,l(o,d),t} = \alpha + \beta logHHI_{l(o,d),t} + \delta_{l(o,d)} + \phi_{d,t} + \tau_i + \epsilon_{l(o,d),t}, \quad (2)$$

in which $Y_{i,l(o,d),t}$ is the (monthly) wage of worker i in local labour market $l(o,d)$, corresponding to occupation o and district d, in year t; and $HHI_{l(o,d),t}$ is the Herfindhal–Hirschman index of the same local labour market $l(o,d)$ and year t. $\delta_{l(o,d)}$ are fixed effects for each local labour market, $\phi_{d,t}$ are district-by-year fixed effects, and τ_i are worker fixed effects. While we do not control specifically for local labour market tightness (Azar et al., 2022), all specifications include both district-by-year (district–year pairs, $\phi_{d,t}$) and local labour market (occupation–district pairs, $\delta_{l(o,d)}$) fixed effects. Given our log–log specification, the estimate of β will indicate the elasticity of the individual wage with respect to the Herfindhal index of the market where the worker is based in each year.

We consider three specifications: the first without controlling neither for worker nor firm fixed effects, the second controlling only for worker fixed effects, and the third controlling for both worker and firm fixed effects. Highly-concentrated labour markets may derive their concentration from the presence of large firms that will tend to have both higher productivity and stronger product market power. These dual advantages may then be shared with workers via collective bargaining, for instance.

For each specification, in order to provide a comprehensive analysis of the effects of labour market concentration on wages, we consider two different measures of HHI: one based on employment stocks (odd columns, in the following tables), and another based on employment flows (even columns). While the former measure may provide a more stable measure of HHI, the latter may be more directly linked to the dynamics in the labour market in each year. The flows measure may thus better reflect the opportunities for wage growth of incumbent workers, for instance through mobility to other firms.

Table 3 presents the first set of results, covering the full 1986–2019 period (and about 70 million worker–year observations). In columns 1 and 2, we exclude worker fixed effects to obtain estimates equivalent to those derived from pooled worker data. In the first column, we find a significantly positive elasticity of 0.018 when using the stock measure of HHI. These results are partially at odds with the view that employer concentration erodes wages but are consistent with the perspective that employer concentration can be a proxy for rent sharing, for instance through (collective) wage bargaining. When controlling for worker fixed effects the magnitude of the coefficient of the stock measure drops considerably to −0.002 (column 3). This drop suggests that high-wage workers tend to be employed in high-concentration local labour markets and that rent sharing can again be relevant in shaping the wage distribution. The point above is less evident when using the flow measure, since including worker fixed effects leads to a much smaller drop, from an elasticity of −0.001 (not statistically significant) to −0.004 (respectively, columns 2 and 4).

Finally, we examine the role of firms in wages and their potential confounding effect. In what is our main specification, we add firm fixed effects to our equation. Joint identification of firm and worker effects is based on mobility of workers across firms and regions over time. In this case, when we include firm fixed effects (columns 5 and 6), both coefficients remain relatively stable. Thus, firm-level unobserved heterogeneity does not appear to be relevant for now.

One may argue that concentration measures are not exogenous with respect to wages. For instance, larger local labour markets (typically with lower concentration levels) may attract more productive firms that pay higher wages and want to be able to hire workers more quickly. While we control for time-invariant differences across local labour markets and for economy-wide year effects at the district level, our results could be influenced by labour demand or labour supply shocks at the level of the local labour market. An increase in the number of university graduates in particular occupations may lead to both lower levels of concentration (if they create new firms) and lower wages in the resulting jobs (due to an increase in labour supply), generating a spurious downward bias in our estimates. Declines in the international demand for specific products may lead to both lower labour demand and lower wages, as in the context of a 'China shock' (Cabral et al., 2021), and more concentrated employment in specific occupations, as some firms exit the market, generating an upward bias in this case.

We address this potential endogeneity issue by instrumenting $HHI_{l(o,d),t}$, following Azar et al. (2022) and earlier research in industrial organisation and labour economics. Our instrument corresponds to the average of the number of employers in the same occupation and year but different region. Formally, it corresponds to $\sum_e log(1/N_e)/29$, where N_e indicates the number of firms in each one of the other (29) regions ('distritos'), except d, that employ workers of the same occupation o, in the same year t. This instrumental variable does not depend directly on market shares as it is based on the number of firms and not their employment. Moreover, it provides variation in local labour market concentration driven by changes across the country except for the specific local labour market that is being instrumented. In this way, we can obtain estimates that are not biased by the local labour demand or labour supply shocks mentioned above.

Table 4
Wage results, IV, 1986–2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Log Herfindhal Index (Stocks)	0.076		−0.006		−0.014	
	(0.006)***		(0.003)*		(0.002)***	
Log Herfindhal Index (Flows)		0.075		−0.007		−0.014
		(0.006)***		(0.003)*		(0.002)***
N	69 328 824	68 185 800	69 328 824	68 185 800	69 328 824	68 185 800
adj. R^2	0.587	0.583	0.785	0.783	0.818	0.817
F	178.58	152.3	3.449	3.55	40.9	38.21
(District x Year) FEs	1	1	1	1	1	1
(Occupation x District) FEs	1	1	1	1	1	1
Firm FEs	0	0	0	0	1	1
Worker FEs	0	0	1	1	1	1
Auxiliary regression (First-stage)						
Log inverse of number of firms	0.64970	0.63685	0.62552	0.61747	0.60023	0.57648
	(0.030)***	(0.029)***	(0.025)***	(0.025)***	(0.021)***	(0.021)***
N	69 328 824	68 185 800	69 328 824	68 185 800	69 328 824	68 185 800
adj. R^2	0.959	0.923	0.962	0.924	0.966	0.928
F	460.5	476.3	604.9	611.2	785.2	766
Kleibergen–Paap rk Wald F-stat	460.5	476.3	604.9	611.2	785.2	766
P-value	0	0	0	0	0	0
Shea's R2	.1225	.07359	.1148	.06599	.1012	.05273

Notes: The columns in the top panel present different specifications of wage equation (2). The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above – see Table 1 – based on either employment stocks (odd columns) or flows (even columns). '(District x Year) FEs' denote fixed effect for each district–year pair. '(Occupation x District) FEs' denote fixed effect for each district–occupation pair. '1' denotes that the set of instruments in the row is included in the specification. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but other districts. Standard errors clustering at the local labour market level. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 4 presents our first set of IV results using the variable above. In the first stage regression, we find the positive (and highly significant) effects predicted. The higher the average number of firms employing workers of the same occupation in other regions, the lower the value of the instrument, and the lower the level of concentration in the local labour market. In the second stage, when not controlling for worker fixed effects (columns 1 and 2), we find again significant positive effects when using the stock measure (elasticity of 0.76) and the new hires measure (elasticity of 0.75).[14] When we introduce worker fixed effects, the elasticity becomes negative, ranging between −0.006 (column 3) and −0.007 (column 4). Both are statistically significant at the 10% level.

Finally, we add firm fixed effects to our equation to control for the forces above. Joint identification of firm and worker effects is based on mobility of workers across firms and regions over time. Columns 5 and 6 in Table 4 present the results of this more comprehensive specification, in which we find negative elasticities of −0.014 for both measures of HHI. This increase in (the absolute value of) the elasticities is consistent with our discussion above that relatively high-wage firms tend to be more common in high-concentration local labour markets. Such correlation can introduce an upward bias in the wage-concentration elasticities that may make one underestimate the overall negative effect of concentration on wages. Given the same interquartile range of 510 HHI points presented in Section 3 and its resulting difference of 2.49 log points (Table A.2), these results indicate that workers that would move from low- to high-concentration local labour markets (defined here as the 25th and 75th percentiles, respectively) would experience a drop in wages of approximately 3.5%. Also, it is worth noting that our coefficients are about ten times lower than the benchmark results in Azar et al. (2022), who find elasticities between −0.116 and −0.2.

[14] In appendix Table A.3, we also run the IV regressions at the local labour market level. When controlling for local labour market fixed effects we obtain a negative elasticity (columns 1 and 2), which becomes positive when we introduce district-by-year fixed effects (columns 3 to 6). The positive sign of the latter estimates is consistent with the results from worker-level regressions that do not control for worker or firm fixed effects (columns 1 and 2 of Table 4).

4.1. Robustness

We now test whether the wage effects above are robust to considering instead each of the seven alternative measures of labour market concentration presented in Section 3.1. Again, this robustness exercise seeks to exploit the richness of our data and provide comparisons that are not feasible with other data sets.

These results are presented in Table 5 and are based on our main specification including worker and firm fixed effects and instrumenting labour market concentration. In columns 1 to 4, we study the impact of aggregating occupations at different levels. Interestingly, we find that wage effects increase as we use more aggregated classifications of occupations. When we define labour markets using collective bargaining job titles (columns 1 and 2), elasticities range from −0.003 to −0.005 (not statistically significant), and are considerably lower than the benchmark case (−0.014). However, if we consider 4-digit occupations (instead of the 5-digit level used in the benchmark case), the estimated results nearly double (columns 3 and 4). These results point to the importance of defining precisely the local labour market. Considering extremely narrow classifications, such as collective bargaining job title codes, overestimates labour market concentration as it separates occupations which are close substitutes to firms. This overestimation of concentration, which may be regarded as a form of measurement error, leads to lower wage effects, even in IV models.

Next, in columns 5 and 6, we consider less aggregated regions. Unlike in the previous case, considering 'concelhos' instead of 'distritos' does not alter our results significantly. Similarly, considering a shorter time window to define a new hire leads to the same elasticity found before (column 7). On the contrary, computing HHI in flows using job-to-job new hires only (column 8) leads to an elasticity of −0.015, indicating that wage markdowns are higher in this context.

In addition, public-sector firms, such as post or railways, may not exercise their monopsony power in the same way as private firms. This is corroborated by our findings in columns 9 and 10, where we do not consider firms with a positive level of public ownership. We obtain slightly higher elasticities (in absolute value) than in the benchmark case. Alternatively, if we exclude firms with fewer than ten employees, we again find a modest increase in the absolute value of the HHI coefficients to about −0.017.

Table 5
Wage results, IV, different measurement approaches, 1986–2019.

	Coll. barg. titles		4-digit occupation		Less agg regions		6-month hiring	Hiring from different firm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Herfindhal Index (Stocks)	−0.003		−0.024		−0.015			
	(0.002)		(0.003)***		(0.003)***			
Log Herfindhal Index (Flows)		−0.005		−0.025		−0.014	−0.014	−0.015
		(0.003)		(0.004)***		(0.003)***	(0.002)***	(0.003)***
N	66 147 032	59 496 992	69 345 193	68 924 363	69 329 930	67 105 344	67 953 166	63 981 829
adj. R^2	0.820	0.811	0.817	0.816	0.820	0.816	0.817	0.839
F	1.549	2.932	54.96	51.06	23.65	16.65	38.19	34.12
Kleibergen–Paap rk Wald F-stat	2212	1364	293.8	958.7	464.1	322.0	750.7	710.7
Shea's R2	.1008	.05153	.07499	.03357	.09423	.0487	0.5151	.0543
	Firms without public equity		10+ employee firms		Manufacturing sector		Industry as occ	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log Herfindhal Index (Stocks)	−0.016		−0.017		−0.023		−0.035	
	(0.002)***		(0.003)***		(0.003)***		(0.007)***	
Log Herfindhal Index (Flows)		−0.017		−0.018		−0.024		−0.037
		(0.002)***		(0.004)***		(0.004)***		(0.008)***
N	64 820 256	64 013 962	55 072 549	53 806 618	20 093 288	19 339 698	67 105 344	66 508 564
adj. R^2	0.809	0.808	0.826	0.824	0.872	0.852	0.814	0.812
F	55.52	52.11	27.16	25.13	45.30	36.38	25.52	23.63
Kleibergen–Paap rk Wald F-stat	892.7	722.8	658.8	450.6	471.0	357.0	600	253.8
Shea's R2	.0969	.0524	.0821	.0395	.09369	.04022	0.4045	.0161

Notes: The columns in the top panel present different specifications of wage equation (2). The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the each different measurement presented in Table 2 based on either employment stocks (odd columns) or flows (even columns). All regressions include district-by-year, district-by-occupation, worker, and firm fixed effects. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but other districts. Standard errors clustering at the local labour market level. Significance levels: * 0.10, ** 0.05, *** 0.01.

Finally, we restrict our analysis to the manufacturing sector or instead use industry and not occupations to define a local labour market (Benmelech et al., 2022; Rinz, 2022). We find that the coefficients increase considerably (in absolute value) in both cases (columns 10 to 13), especially the latter. These elasticities range between 2.3% and 3.7%.[15]

Overall, our results from this subsection highlight important dimensions of stability but also of differentiation in the effects of labour market concentration on wages. While virtually all approaches indicate negative effects, methodological choices or constraints can affect the magnitude of the effects, in some cases doubling their magnitude.

4.2. Extensions

In the analysis above we have established that employer concentration has a negative impact on wages, even when using different measurement approaches and samples. Here, we extend our analysis to four additional issues: (*i*) the potential attenuation of market power effects through collective bargaining; (*ii*) the role of large firms in concentrated markets; (*iii*) potential non-linear effects of concentration on wages; and (*iv*) the impact of market power on wage inequality.

Collective bargaining

In our main analyses above, the introduction of firm fixed effects led to a substantial increase in the (negative) effect of labour market concentration on wages, highlighting the relevance of firm heterogeneity. One point potential factor that may be capture by these fixed effects is the role of unionisation or collective bargaining in wage determination. Indeed, in the same way that workers faced with a dominant employer in their local labour market will not have many job alternatives, a dominant employer faced with a powerful union may find it difficult to replace their workers. Such employer will then have to share at least some of its rents with its workers, particularly when the firm has not only labour market power but also product market power.

Such countervailing, trade-union-based mechanism would potentially lead to a more balanced relationship between the employer and the employee sides. In this case, the wage setting power of the employer is attenuated and the rent sharing dimension may even possibly gain greater predominance (see Card et al. (2018) and Garin and Silverio (2023) for recent evidence of rent sharing in Portugal, also based on the QP data set.) Note that, as in other European countries, collective bargaining plays an important role in the labour market of Portugal (Martins, 2021; Martins and Saraiva, 2020).[16] Local labour markets may also be associated to industrial clusters, generating external scale economies, leading to higher wages (see Figueiredo et al. (2014), which uses the same data set as in this paper).

To test whether collective bargaining is indeed an important force in counter-acting employer market power, we interact our measures of concentration with the average collective bargaining coverage of each local labour market over the entire period. Similarly, we instrument this interaction using the interaction between bargaining coverage and the previous instrument. We use the average and not the contemporaneous level of coverage to avoid any correlation between our instrument and wages, except, of course, through the instrumented variable. Our motivation is that the wage markdown resulting from increasing employer concentration (and the resulting fewer employer alternatives for workers) may lead to the emergence or strengthening of unionisation and collective bargaining. Such emergence may be particularly important when employers also coordinate, namely through employers' associations (Martins, 2020).

Table 6 presents the results. Interestingly, when we account for collective bargaining, the elasticities without firm fixed effects (columns

[15] On the robustness of our findings in terms of the time dimension, when comparing the current findings for 1986–2019 to those of the period 1991–2013 (Martins, 2018), we find that they are very similar. This indicates that the effects of concentration on wages have not changed significantly over the last four decades.

[16] Despite low unionisation rates, collective agreements are frequently extended by the government, requiring most firms and employees in a given industry to follow these agreements even for workers that are not unionised. As to other labour institutions that may also affect wage determination, the most important include minimum wages and unemployment benefits. While the former were relatively low in Portugal until 2006, unemployment benefits were always relatively generous, in terms of replacement rates and maximum duration.

Table 6
Wage results, IV, Collective Bargaining, 1986–2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Log Herfindhal Index (Stock)	0.151		−0.026		−0.013	
	(0.030)***		(0.015)*		(0.010)***	
Log Herfindhal Index (Flow)		0.174		−0.008		−0.015
		(0.034)***		(0.016)*		(0.011)
% of workers with CB in LLM x Log Herfindhal Index (Stock)	−0.089		0.024		−0.002	
	(0.033)***		(0.018)		(0.012)	
% of workers with CB in LLM x Log Herfindhal Index (Flow)		−0.116		0.026		−0.001
		(0.037)**		(0.020)		(0.013)
N	27 741 895	27 285 637	27 741 895	27 285 637	27 741 895	27 285 637
adj. R^2	0.587	0.583	0.785	0.783	0.822	0.821
F	390.5	356.7	136.4	126.4	21.6	20.38
Kleibergen–Paap rk Wald F-stat	99.1	75.0	207.7	114.9	568.1	436.8
(District x Year) FEs	1	1	1	1	1	1
(Occupation x District) FEs	1	1	1	1	1	1
Firm FEs	0	0	0	0	1	1
Worker FEs	0	0	1	1	1	1

Notes: The columns in the top panel present different specifications of wage equation (2). The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above – see Table 1 – based on either employment stocks (odd columns) or flows (even columns). '(District x Year) FEs' denote fixed effect for each district–year pair. '(Occupation x District) FEs' denote fixed effect for each district–occupation pair. '1' denotes that the set of instruments in the row is included in the specification. The instruments are the average of the log of the inverse of the number of firms in the same occupation and year but other districts and its interaction with the local labour-market's average coverage of collective bargaining. Standard errors clustering at the local labour market level. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 7
Wage results, IV, Local labour market leader, 1986–2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Log Herfindhal Index (Stock)	0.073		−0.006		−0.014	
	(0.006)***		(0.003)*		(0.002)***	
Log Herfindhal Index (Flow)		0.073		−0.007		−0.015
		(0.006)***		(0.004)*		(0.002)***
LLM top 5 employer x Log Herfindhal Index (Stock)	−0.044		−0.012		−0.002	
	(0.003)***		(0.001)***		(0.001)***	
LLM top 5 employer x Log Herfindhal Index (Flow)		−0.063		−0.017		−0.005
		(0.004)***		(0.002)***		(0.001)***
N	27 741 901	27 285 652	27 741 901	27 285 652	27 741 901	27 285 652
adj. R^2	0.588	0.583	0.785	0.783	0.822	0.821
F	936.3	868	200.2	196.2	21.02	24.51
Kleibergen–Paap rk Wald F-stat	226.5	232.2	297.8	297.1	389.7	367.5
(District x Year) FEs	1	1	1	1	1	1
(Occupation x District) FEs	1	1	1	1	1	1
Firm FEs	0	0	0	0	1	1
Worker FEs	0	0	1	1	1	1

Notes: The columns in the top panel present different specifications of wage equation (2). The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above – see Table 1 – based on either employment stocks (odd columns) or flows (even columns). '(District x Year) FEs' denote fixed effect for each district–year pair. '(Occupation x District) FEs' denote fixed effect for each district–occupation pair. '1' denotes that the set of instruments in the row is included in the specification. The instruments are the average of the log of the inverse of the number of firms in the same occupation and year but other districts and its interaction with the dummy for working for a top 5 employer in the local labour-market. Standard errors clustering at the local labour market level. Significance levels: * 0.10, ** 0.05, *** 0.01.

3 and 4) are actually higher (in absolute terms) than those with such fixed effects (columns 5 and 6). This suggests that greater levels of co-ordination between employees can indeed attenuate wage markdowns. This finding is in line with Benmelech et al. (2022) and Dodini et al. (2021), who also find that unionisation counteracts the wage effect of labour-market concentration. There is also evidence for Germany and Portugal that higher levels of industry-level bargaining coverage attenuates markdowns (Bassanini et al., 2023a).

Local labour-market leaders

We also examine the impact of firm size on wage effects. As Boal and Ransom (1997) note, in an asymmetric Cournot model, larger firms may be able to impose larger wage reductions. However, this may not be the case if we consider models with random search or worker heterogeneity in preferences for firm amenities (Card et al., 2018). In fact, according to the latter models, large firms operating in smaller markets might have less market power than small firms in large markets due to the smaller pools of workers, making it difficult to employ those who value their specific amenities.

To examine this question, we interact our measures of labour-market concentration with a dummy equal to one when a firm is a local market leader. Such leaders are defined as a top five employer in a local labour-market in a year. In our preferred specifications in Table 7 (columns 5 and 6), the coefficient of the interaction term ranges between −0.002 and −0.005 (both are statistically significant at the 1% level). This means that markdowns are 15% to 30% higher for local leaders compared to their smaller counterparts. Our analysis therefore supports the scope for larger firms to impose larger wage reductions

Table 8
Wage results, IV, 1986–2019 — results per HHI quartile.

	First quartile		Second quartile		Third quartile		Fourth quartile	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Herfindhal Index (Stocks)	−0.020		−0.042		−0.062		−0.030	
	(0.014)		(0.012)***		(0.009)***		(0.007)***	
Log Herfindhal Index (Flows)		−0.035		−0.069		−0.112		−0.032
		(0.015)**		(0.019)***		(0.033)***		(0.005)***
N	15 822 974	16 232 508	17 526 045	16 967 530	17 878 959	17 414 758	18 102 190	17 578 472
adj. R^2	0. 862	0.863	0.844	0.844	0.844	0.822	0.836	0.838
F	2.171	5.526	12.7	13.52	45.28	11.69	16.27	37.7
Kleibergen–Paap rk Wald F-stat	40.98	45.29	118.9	53.14	241.7	48.23	1097	755.2
Shea's R2	.0629	.0394	.0349	.0113	.0383	.0067	.0650	.0251

Notes: The columns in the top panel present different specifications of wage equation (2). Columns 1 and 2 only use observations belonging to the first quartile of the HHI distribution. Columns 3 and 4 only use observations belonging to the second quartile of the HHI distribution. Columns 5 and 6 only use observations belonging to the third quartile of the HHI distribution. Columns 7 and 8 only use observations belonging to the four quartile of the HHI distribution. The dependent variable is the log of the local labour market mean of individual total wages. The Herfindhal index corresponds to the benchmark model presented above – see Table 1 – based on either employment stocks (odd columns) or flows (even columns). All regressions include district-by-year, district-by-occupation, worker, and firm fixed effects. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but other districts. Standard errors clustering at the local labour market level. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 9
Wage results, IV, Inequality, 1986–2019.

Panel A	Within firm					
	P90/P10		P90/P50		P50/P10	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Herfindhal Index (Stocks)	0.141		0.0527		0.0529	
	(0.023)*		(0.001)***		(0.020)***	
Log Herfindhal Index (Flows)		0.153		0.0565		0.0578
		(0.024)**		(0.001)***		(0.021)***
N	7 256 237	7 231 318	7 256 237	7 231 318	7 256 237	7 231 318
adj. R^2	0.126	0.126	0.264	0.263	0.1130	0.1130
F	38.59	40.05	3847	3950	7.14	7.54
Kleibergen–Paap rk Wald F-stat	766 202	809 680	766 202	809 680	766 202	809 680
Shea's R2	.4802	.4394	.4802	.4394	.4802	.4394
Panel B	Within local labour markets					
	P90/P10		P90/P50		P50/P10	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Herfindhal Index (Stocks)	−0.261		−0.170		0.024	
	(0.143)*		(0.006)***		(0.130)	
Log Herfindhal Index (Flows)		−0.166		−0.106		−0.003
		(0.037)***		(0.008)***		(0.018)
N	449 881	301 189	449 881	301 189	449 881	301 189
adj. R^2	0.0819	0.3116	0.4346	0.4609	0.0791	0.2548
F	3.33	20.34	847.3	170.4	0.033	0.0258
Kleibergen–Paap rk Wald F-stat	14 935	10 534	14 935	10 534	14 935	10 534
Shea's R2	.2278	.1516	.2278	.1516	.2278	.1516

Notes: The columns in the top panels present different specifications of wage equation (2). The dependent variables are the ratio between the 90th and the 10th wage percentiles (columns 1 and 2), the ratio between the 90th and the 50th wage percentiles (columns 3 and 4), and the ratio between the 50th and the 10th wage percentiles (columns 5 and 6). Panel A uses wage percentiles to describe how wages are distributed within firms, while in Panel B they describe how wages are distributed within local labour-markets. The Herfindhal index corresponds to the benchmark model presented above – see Table 1 – based on either employment stocks (odd columns) or flows (even columns). In panel A the Herfindhal is the average concentration level across all workers in the firm, instrumented by the average value of the instrument within the firm. In panel B the Herfindhal is the same as the one used in the main analysis. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but in other districts. All regressions in panel A include firm and district-by-year fixed effects. In panel B, regressions control for district-by-occupation and district-by-year fixed effects. Standard errors clustering at the firm level in panel A and at the local labour market level in panel B. Significance levels: * 0.10, ** 0.05, *** 0.01.

on their employees, when compared to smaller firms in the same local labour market.

Non-linear effects

The effects of labour-market concentration are not necessarily linear. This idea is supported by the findings of Azar et al. (2023) and Munguía Corella (2020), who find that the impact of minimum wage policies on employment varies depending on the level of labour concentration. Here, we examine potential non-linearities in wage effects instead of employment. For instance, the relatively small wage effects that we find may reflect the fact that most of our HHI distribution lies at relatively low concentration levels. Wage effects may be considerably higher at higher HHI levels.

We approach this question by conducting our analysis separately at each quartile of the (employment-weighted) HHI distribution. The results, presented in Table 8, support the case of non-linearities. In columns 1 and 2, regarding the first quartile, we find larger elasticities (in absolute value) than the ones we present in our baseline regressions. However, these estimates are less precise, likely due to the little variation in HHI within the first quartile — the HHI in stocks (flows) is between 1 and 46 (0 and 88). (See Table A.2 for more detailed descriptive statistics on the HHI distribution. The concentration ranges increase dramatically as we consider higher quartiles.) Regarding the second quartile (columns 2 and 4), we document statistically significant elasticities (at the 1% level) ranging between −0.042 (stocks) and −0.069 (flows). Elasticities are even greater in third quartile (columns

5 and 6), between −0.062 and −0.112 (significant at the 1% level). Finally, for the fourth quartile (columns 7 and 8) we find much smaller elasticities, between −0.030 and −0.032 (both significant at the 1% level). Furthermore, we also find that all these results are robust to removing public-sector firms – Table A.4. This is motivated by the fact that public-sector firms are typically located in high levels of concentration and the possibility that they respond differently to the same level of concentration, as they may not profit maximise in the same way as private-sector firms.

Overall, these results suggest that the wage effects of concentration are non-linear in the concentration distribution, increasing up to the third quartile and decreasing in the fourth quartile. These results also indicate that our main findings are shaped by the middle of the concentration distribution, where changes in concentration may have more pronounced effects than cases in which the concentration is already high — such as the fourth quartile.

Inequality

Finally, we study whether labour-market concentration may influence wage inequality both within firms and within local labour markets (Rinz, 2022; Dodini et al., 2021). There are potentially many mechanisms in such complex relationship. For example, if workers are paid the (statutory or collective bargaining) minimum wage, firms may have limited power to influence their wages (assuming no disemployment effects). In this case, workers with higher wages would be more vulnerable to labour concentration, meaning that wage inequality could decrease as concentration increases. Different workers may also be distributed differently within firms and local labour markets, leading to potentially different effects of concentration on the two types of inequality.

To analyse these effects, even if only tentatively, we consider the ratios between the 90th and the 10th percentiles (P90/P10), the 90th and the 50th percentiles (P90/P50), and the 50th and the 10th percentiles (P50/P10). In the within-firm analysis, we consider the average level of labour-market concentration in the firm (across all its workers), while in the local labour-market analysis we use the same concentration measures as in our main analyses above.

Our results – Table 9 – indicate that within-firm inequality increases with labour concentration. In contrast, inequality within local labour-markets decreases with concentration. Specifically, the coefficients in columns 1 and 2 of panel A indicate that an increase in HHI by 1% increases the P90/P10 ratio from 7% to 8%. These coefficients are twice the magnitude of the effects of labour concentration on the P90/P50 and the P50/P10 ratios, at around 4%. This larger increase in inequality between the top and bottom percentiles can have different explanations. It could be due to firms sharing their monopsony rents with top managers in the firm, as suggested by Rinz (2022), or, for instance, because wages stagnate at the bottom of the wage distribution (within the firm).

Regarding inequality within local labour-markets, increases in concentration by 1% lead to a decrease of between 5 to 10% in the P90/P10 ratio, and between 7 to 11% in the P90/P50 ratio. We find no effect of labour-market concentration on the P50/P10 ratio. One possible explanation is that, as mentioned above, there is not much room to adjust wages at the bottom of the wage distribution, possibly due to the minimum wage or collective bargaining agreements. Overall, we regard the analysis of the relationship between labour market concentration and wage inequality to be a promising topic for further research.

5. Conclusions

Exploiting rich matched data for Portugal, we made a number of contributions to the literature on local labour market power and its wage effects. Our evidence supports the significance of employer labour concentration, in terms of both its magnitude and wage implications. First, we find that at least 8% of workers can be regarded to be exposed to concentration levels assumed to raise (product) market power concerns. We also find that this percentage has remained relatively stable over a 34-year period but can vary significantly depending on methodological choices (or data availability). Second, we estimate wage-concentration elasticities that are significantly negative, at around −1.4%. This estimate implies that workers that would move from the bottom to the top quartiles of the concentration distribution could see their wages fall by about 3.5%.

All in all, our results suggest that employer market power may be an important even if not necessarily major driver of wage inequality. In fact, while we find concentration to increase wage inequality within firms, the relationship changes when we analyse inequality within local labour-markets. Also, the smaller elasticities that we document here, when compared to the U.S., may follow from the different labour institutions in the two countries. In particular, sectoral collective bargaining in Portugal sets common industry wage floors across multiple regions and jobs, regardless of the specific conditions of the local labour market, including its concentration level. These practices are common in many European countries but largely not applicable in the U.S. On this point, we find suggestive evidence that collective bargaining counteracts the negative effect of employer concentration.

From a methodological perspective, our findings highlight the different sensitivity of concentration measures with respect to data choices or constraints, including the sector under analysis, the focus on employment flows or stocks, and the level of aggregation of occupations and geographical areas. For instance, we find that concentration measures can more than double depending on the approach adopted. Given the relative novelty of measuring concentration in local labour markets, these estimates may also inform policy makers that wish to establish critical thresholds suitable to address monopsony.

Our results also underline the importance of taking into account both the worker and the firm heterogeneity dimensions when estimating wage-concentration elasticities. Several high-concentration labour markets are characterised by larger and more productive firms, which tend to pay higher wages and employ more skilled workers. As we show in our results, these factors can bias estimates towards zero or even positive effects.

Finally, from a policy angle, our results underline the relevance of labour markets for competition agencies — and that of competition concerns for labour institutions. Higher labour market concentration can have a detrimental effect on wages, as employers may take advantage of their market power. Even in a generally regulated labour market as Portugal, wages are depressed by weaker competition. This implies that, for instance, firm mergers may have competition implications that extend beyond product markets. This is particularly important since we find that concentration and its interaction with firm size lead to higher wage markdowns. Moreover, employers' associations may also deserve greater attention from both competition and labour authorities. Employers' associations may promote collusion across firms operating in the same industry and be an important driver of the negative wage effects documented here.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Fig. A.1 and Tables A.1–A.4.

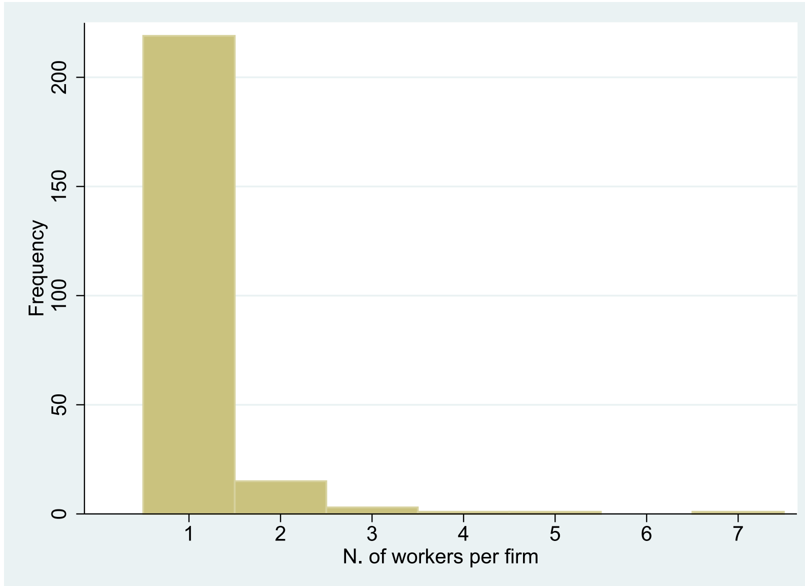

Fig. A.1. Appendix: Case study: Distribution of workers per firm, Construction/public works technician, Leiria district, 2006. **Notes:** Own calculations based on the 'Quadros de Pessoal' data set. Analysis of a particular occupation (Construction and public works technician, code 31120) in a particular district (Leiria) in a particular year (2006). Each observation in the histogram corresponds to one of 240 firms located in the district that employ at least one worker with this occupation in that year. The Herfindhal index (which ranges between 0 and 10,000) for this local labour market in this year is 52.7.

Table A.1
HHI values (weighted and unweighted), 1985–2019.

Year	HHI (workers)		HHI (hires)		N. cells	N. workers	N. hires
	Unweighted	Weighted	Unweighted	Weighted			
1985	4852.4	1023.7	2743.5	1166.7	6219	876 559	80 589
1986	4998.1	904.4	2755.6	816.0	11 133	1 677 977	206 893
1987	5045.6	912.3	2830.8	727.4	11 249	1 706 841	246 613
1988	4963.5	857.5	2923.3	695.6	11 288	1 751 868	303 258
1989	4968.8	819.9	3074.7	727.7	11 584	1 902 171	364 735
1991	4854.1	769.6	3029.5	695.9	11 704	1 963 350	374 348
1992	4816.9	735.5	2966.9	705.2	11 666	1 986 647	359 127
1993	4780.5	692.1	2911.7	723.3	11 690	1 980 966	327 438
1994	4753.9	704.0	2868.1	808.4	11 722	1 927 972	321 427
1995	4515.4	752.6	3164.4	996.5	13 323	1 993 603	339 957
1996	4591.7	817.1	3142.4	1032.6	13 327	1 968 477	346 704
1997	4503.2	794.7	3244.2	971.5	13 696	2 150 737	438 352
1998	4692.7	823.4	3220.2	930.2	14 889	2 185 320	454 425
1999	4797.8	810.5	3314.8	1014.0	16 224	2 283 315	449 316
2000	4726.8	774.2	3350.8	913.1	16 941	2 494 350	552 783
2002	4635.6	784.9	3480.9	943.8	18 701	2 695 196	584 535
2003	4438.3	750.8	3376.7	1072.4	19 690	2 800 003	540 625
2004	4306.9	727.5	3395.8	1042.4	20 252	2 891 960	569 950
2005	4197.6	698.2	3326.1	977.6	20 656	3 065 839	630 755
2006	4179.6	696.2	3284.0	981.0	20 753	3 111 190	661 384
2007	4141.2	687.6	3293.8	944.9	20 927	3 220 102	742 339
2008	4138.8	708.8	3366.1	1031.2	21 062	3 267 603	763 912
2009	4177.0	726.8	3291.3	1136.1	20 867	3 125 383	623 430
2010	3437.2	626.3	3178.4	968.8	12 214	2 897 224	569 937
2011	3437.8	641.4	3253.5	1089.0	12 185	2 849 773	532 959
2012	3480.2	655.2	3181.9	1126.3	12 148	2 665 448	429 924
2013	3466.9	658.1	3213.1	1079.7	12 013	2 654 089	482 447
2014	3449.0	649.1	3198.8	992.6	12 006	2 732 976	563 518
2015	3456.4	646.5	3163.7	937.7	12 069	2 813 684	619 577
2016	3454.7	647.4	3160.4	967.9	12 090	2 921 037	663 948
2017	3455.2	668.6	3213.7	1022.9	12 107	3 053 565	738 881
2018	3468.5	663.3	3233.0	947.5	12 190	3 173 048	792 708
2019	3481.6	682.6	3247.0	955.9	12 197	3 227 059	808 045

Notes: See the Herfindhal index formula in Eq. (1). HHI (workers) denotes the mean Herfindhal index in each year, either placing equal weights to all district–occupation–year cells (unweighted 'stocks') or considering the distributions of employees across firms in each district–occupation–year cells (weighted 'stocks'). HHI (in flows) denotes the mean Herfindhal index in each year, either placing equal weights to all district–occupation–year cells (unweighted 'flows') or considering the distributions of new hires (workers hired over the previous 12 months, as of October of each year (March in 1991 up to 1993)), across firms in each district–occupation–year cells (weighted 'flows'). 'N. cells' indicates the number of district–occupation pairs in each year. 'N. workers' ('N. hires') indicates the total number of workers (hires) in each year. Figures for 1990 and 2001 are not presented as worker-level data for this year is not available. Occupation codes change in 1995 and 2010. The weights of the two series are the employment count of each occupation–district–year cell.

Table A.2
Descriptive statistics, HHI distribution, 1985–2019.

	Min	P5	P10	P25	P50	P75	P90	P95	Max
HHI (workers)	1.03	11.67	18.79	45.95	141.95	555.91	1722.55	3756.22	10 000
HHI (new hires)	0	19.90	34.84	87.57	279.05	877.44	2669.75	5000	10 000

Notes: Each observation corresponds to a district–occupation–year combination. Each cell carries a weight proportional to its employment.

Table A.3
Wage results, IV, 1986–2019 — results at the local labour market level.

	(1)	(2)	(3)	(4)	(5)	(6)
Log Herfindhal Index (Stocks)	0.024		−0.131		0.042	
	(0.002)***		(0.004)*		(0.003)***	
Log Herfindhal Index (Flows)		0.004		−0.168		0.042
		(0.003)		(0.005)***		(0.003)***
N	449 898	301 194	449 898	301 194	449 898	301 194
adj. R^2	0. 587	0.583	0.785	0.783	0.818	0.817
F	178.58	152.3	3.449	3.55	40.9	38.21
(District x Year) FEs	1	1	0	0	1	1
(Occupation x District) FEs	0	0	1	1	1	1
Auxiliary regression (First-stage)						
Log inverse of number of firms	0.98350	0.83089	0.80411	0.72813	0.75546	0.70842
	(0.004)***	(0.004)***	(0.006)***	(0.007)***	(0.006)***	(0.007)***
N	69 328 824	68 185 800	69 328 824	68 185 800	69 328 824	68 185 800
adj. R^2	0.697	0.631	0.925	0.862	0.926	0.865
Kleibergen–Paap rk Wald F-stat	72 476	47 539	17 392	12 315	14 939	10 543
P-value	0	0	0	0	0	0
Shea's R2	.6545	.5938	.2711	.1762	.2279	.1516

Notes: The columns in the top panel present different specifications of wage equation (2). The dependent variable is the log of the local labour market mean of individual total wages. The Herfindhal index corresponds to the benchmark model presented above – see Table 1 – based on either employment stocks (odd columns) or flows (even columns). '(District x Year) FEs' denote fixed effect for each district–year pair. '(Occupation x District) FEs' denote fixed effect for each district–occupation pair. '1' denotes that the set of instruments in the row is included in the specification. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but other districts. Standard errors clustering at the local labour market level. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table A.4
Wage results, IV, 1986–2019 — results per HHI quartile (only firms without public equity).

	First quartile		Second quartile		Third quartile		Fourth quartile	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Herfindhal Index (Stocks)	−0.021		−0.049		−0.070		−0.027	
	(0.013)		(0.012)***		(0.010)***		(0.006)***	
Log Herfindhal Index (Flows)		−0.029		−0.076		−0.110		−0.036
		(0.013)**		(0.021)***		(0.025)***		(0.006)***
N	14 697 587	15 237 346	16 446 409	15 947 357	16 739 377	16 344 569	16 937 126	16 501 924
adj. R^2	0.863	0.859	0.835	0.841	0.839	0.816	0.820	0.824
F	2.668	5.107	17.53	13.03	44.83	19.14	18.33	41.44
Kleibergen–Paap rk Wald F-stat	35.71	155.5	51.34	40.5	176	60.74	883.8	817.7
Shea's R2	.1289	.0815	.0384	.0106	.0351	.0094	.0670	.0242

Notes: The columns in the top panel present different specifications of wage equation (2). Columns 1 and 2 only use observations belonging to the first quartile of the HHI distribution. Columns 3 and 4 only use observations belonging to the second quartile of the HHI distribution. Columns 5 and 6 only use observations belonging to the third quartile of the HHI distribution. Columns 7 and 8 only use observations belonging to the four quartile of the HHI distribution. The dependent variable is the log of the local labour market mean of individual total wages. The Herfindhal index corresponds to the measure that uses only firms without public equity – as presented in row 7 in Table 2 – based on either employment stocks (odd columns) or flows (even columns). All regressions include district-by-year, district-by-occupation, worker, and firm fixed effects. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but other districts. Standard errors clustering at the local labour market level. Significance levels: * 0.10, ** 0.05, *** 0.01.

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