Making their own weather?

Estimating employer labour-market power and its wage effects*

Pedro S. Martins†

Queen Mary University of London

& NovaSBE & IZA & GLO

December 30, 2019

Abstract

The subdued wage growth observed over the last years in many countries has spurred renewed interest in monopsony views of the labour market. This paper is one of the first to measure the extent and robustness of employer labour-market power and its wage implications exploiting comprehensive matched employer-employee data. We find average (employment-weighted) Herfindhal indices of 800 to 1,100; and that less than 9% of workers are exposed to concentration levels thought to raise market power concerns. However, these figures can increase significantly with different methodological choices. Finally, when controlling for both worker and firm heterogeneity and instrumenting for concentration, wages are found to be negatively affected by employer concentration, with elasticities of around -1.5%.

Keywords: Oligopsony, Wages, Portugal.

JEL Codes: J42, J31, J63.

*The author thanks Andrea Bassanini, Wenjing Duan, Judite Goncalves, Juan Jimeno, Claudio Lucifora, Ioana Marinescu, Bledi Taska and workshop participants at Queen Mary University of London and the European Commission for comments. The author also thanks INE and the Ministries of Education and Employment, Portugal, for data access, and the European Union for financial support (grant VS/2016/0340).

†Email: `p.martins@qmul.ac.uk`. Web: `https://sites.google.com/site/pmrsmartins/`. Address: School of Business and Management, Queen Mary University of London, Mile End Road, London E1 4NS, United Kingdom. Phone: +44/0 2078822708.

1 Introduction

The limited wage growth observed in many countries in the recovery following the 2008 financial crisis has prompted important questions about the degree of wage setting power enjoyed by employers. These questions have gathered additional momentum with the complementary evidence that has emerged over the last decade on declining labour shares, the rise of 'superstar firms' (Autor et al. 2017), the relevance of 'no poaching agreements' in employment contracts (Krueger & Ashenfelter 2018), and the limited disemployment effects of minimum wages. While these findings may still be reconciled with largely competitive labour markets, the relevance of evidence on employer labour-market power is clear.

This paper contributes to the literature on monopsony (Staiger et al. 2010, Manning 2010, 2011, Falch 2010, Matsudaira 2014, Card et al. 2018) by addressing two major questions: 1) how concentrated are local labour markets? and 2) what is the impact of concentration on wages? We believe we are the first to address these questions by exploiting rich matched employer-employee data. Our data covers the full population of workers (and occupations) in a country, Portugal, including not only manufacturing but also services as well as both incumbent workers and new hires. Furthermore, in contrast to other papers in this literature, our data also includes information on the occupation, region and wages of each worker. All these variables are particularly detailed and comparable not only across firms but also over time, during the 23-year period that we cover.

These two data dimensions - 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 in this research) and concentration levels may be much higher in manufacturing than services. Moreover, a less than comprehensive knowledge of the spread of comparable occupations across firms as well as an analysis based exclusively on employment flows or stocks may also lead to overestimated measures of concentration.

A key reference in this literature is Azar et al. (2017) (see also Azar et al. (2018)): 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: cuts of 17% from moving from the 25th to the 75th percentile of the Herfindhal distribution.[1]

Our results are consistent with the previous literature in that we also find that employer market power is a significant phenomenon. However, our results indicate that employer market power effects are smaller than in earlier evidence that could not draw on data with the same level of detail. This finding of smaller effects applies both in terms of the percentage of the workforce employed in high-concentration local labour markets and in terms of 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 market power concerns (DoJ/FTC 2010). However, we also show that these measures can more than double with different methodological choices, in particular when considering more detailed occupation codes and more disaggregated geographical areas.

Our wage analysis highlights the relevance of controlling for worker (and firm) composition. When not doing so, 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 will tend to be more productive and or enjoy higher product market power. These two dimensions will in turn create scope both for stronger selection in hirings (employing workers of higher productivity) as well as rent sharing, through bilateral bargaining, particularly when labour market policies are more supportive of collective bargaining.

We address these factors by again exploiting the richness of our data and estimating the relationship between wages and concentration using both worker and firm fixed effects. We follow closely Azar et al. (2017) 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 -1.5%. 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 2%, a figure significantly smaller than in Azar et al. (2017). This smaller effect may reflect the role of different labour market institutions, in particular sectoral collective bargaining, which is much stronger in Portugal than the U.S, and can erode the negative

[1] See also Benmelech et al. (2018) and Rinz (2018) for two recent contributions focusing on the case of the U.S and Duan & Martins (2019) who also examine the role of employer labour market power in shaping rent sharing in China. The last two papers examine the manufacturing sector only. The three papers examine data that does not provide information on occupations per firm.

effect of employer market power.

The structure of the remaining of the paper is as follows: Section 2 presents the data used. Sections 3 and 4 describe our main measures of employer concentration and a comprehensive sensitivity analysis that we also conduct. The wage effects results are presented in Section 5. Finally, Section 6 concludes.

2 Data

Our empirical 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 individual information on each of their employees and time-invariant firm and worker identifiers. The data set follows from an annual mandatory survey collected by the Ministry of Employment for the purposes of monitoring and enforcing compliance with employment law.

Worker information concerns the month of October of each year and features a number of variables, on an individual basis, the most important for us being the monthly wage (base and total) and the occupation. The latter is defined using the national occupations classification, which features about 1,400 different entries, defined at a six-digit level (the national occupation classification, unchanged between 1995 and 2009). Other worker-level variables that we also consider include the year and month of birth, 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 firm-level, we use the geographical location of the firm (at the 'concelho' level - over 450 different locations - and the more aggregated 'distrito' level - 30 different locations, including the islands of Azores and Madeira).[2]

Our benchmark definition of local labour markets is based on the occupation definition composed of 1,400 entry and the region definition composed of 30 entries ('distritos'). These regions have an average size of about 3,000 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

[2]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. Other worker-level variables available are gender, schooling, hours of work, and type of employment contract. At the firm-level, the data also provides information on industry (five-digit variable), total sales, legal type of firm, capital equity, and type of ownership.

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 and in many cases in less than one hour by public transport as well. 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 14,500 local labour markets (occupation-region pairs) per year over the 22-year period covered, as we discuss below. In our analysis, we consider the years between 1991 and 2013 (except 2001 which is not available).

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 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 Table 1, we present the HHI indices for each year, considering both the cases of employment ('stocks') and of new hires ('flows'). The latter are defined here as workers employed in the firm as of the census month - October of each year since 1994 and March of each year until 1993 - and hired over the previous 12 months. The results indicate that the HHIs in the case of stocks range between 720 and 900, while in the case of flows they range between 700 and 1,150. 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 2,500.[3]

[3] Figure A1 presents an illustration of this approach, focusing on 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 with this occupation in that year. The Herfindhal index for this observation is 52.7, highlighting the significantly dispersed nature of employment of this occupation in this district, as over 200 of the 240 firms employ only one worker in this occupation.

As can be seen from Figure 1, which presents graphically the HHI time series, there is no particular trend that can be discerned from our results, for instance in terms of an increase in labour market concentration over time. If anything, we find some suggestive downward trend, particularly over the period 1998-2010, in the employment stocks measure. The data may also be consistent with moderate counterciclicality, particularly in the hirings 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 hirings during downturns but also the particular distribution of hirings 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 1 indicates that the HHIs in stocks are almost always higher than the corresponding (same year) HHI's in flows. For instance, in 2006, the former is 777 and the latter 1030. Overall, flows HHIs are, on average, 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.

Table 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 hirings in each year. The first series ranges between 10,000 and 20,000 cells, reflecting the growth of the formal sector since the early 1990s and then a change in occupation codes in 2010, as well as the labour market 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 1.9 million employees (320,000 new hires) to 3.3 million employees (760,000 new hires), over the period.

We also describe our data in terms of the nearly 320,000 local labour market cells, pooled over the entire period of our analysis, 1991-2013 - Table 2. The mean number of workers per cell is 176, while the mean number of new hires is 35 (both statistics are not weighted). The mean HHI measures are, when considering employment stocks, 798 (weighted) and 4,205 (unweighted). When considering employment flows (new hirings), these figures are 1,055 and 3,311, respectively. The latter figure is the most comparable with those reported in Azar et al. (2017), based on 16 of the most frequent occupations posted on a large online jobs board in the US over the period 2010-2013, which present a remarkably similar mean HHI figure of 3,157. While Azar et al. (2017) 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 858 HHI points (950 - 92) when weighting cells by employment but much higher, 6,638 (7,551 - 913), when not weighting.[4]. We will consider these figures later, when computing the wage implications of more concentrated markets, together with the elasticities presented in Section 5.

To illustrate in greater detail our findings, the left- and right-hand-side histograms in Figure 2 present 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, respectively. As in the case of the pooled cells, we find that this weighting makes a significant difference to the resulting distributions 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 200 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 Figure A1.

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 1,000 workers in a particular year, 2006, the occupations that are are associated to the lowest levels of concentration are 'Director and managers of small firms' (13110-13199 occupation codes; average HHI of about 30), 'Production director' (12220; 34), and 'Secretary' (41150; 39). 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' (41420; 9,950), 'Train driver' (83110; 9,880), and 'Industrial robot operator' (81729; 9710). The first two cases reflect the fact that the post distribution and train transport industries operate as monopolies in Portugal, as in many other countries.

[4]Standard deviations of HHI measures range between around 1,800 (weighted analysis) and 3,700 (unweighted case), regardless of the type of measure (stock or flow). Furthermore, mean salaries range between 566 and 768 euros, depending on whether one is considering base or total wages and weighted or unweighted means.

4 Sensitivity analysis

The results above follow from choices we made regarding the definition of a local labour market. To investigate the robustness of our findings, in particular the generally low levels of employer labour-market concentration, we exploit the richness of our data set to measure local labour markets in up to five alternative ways. In all cases, we depart from our benchmark model described above (based on 1,400 occupations and 30 districts) and introduce changes in these or other parameters of the analysis. All modifications are deliberately selected so that they are likely to increase concentration measures. In this way, we can better understand what may be the upper bounds of these measures.

In the first alternative approach, we restrict the time window under which a worker is considered a new hiring, from the 12-month period used before to six months only. Our interest in this analysis stems from the vacancy perspective adopted in other papers (Azar et al. 2017, 2018). Table 3, second row, presents the results (the first row presents the benchmark results, weighted by employment, to facilitate the comparison with alternative measurement approaches). We find that the HHI for new hirings increases by 17%, from 1,007 to 1,170 (the employment stocks results are unchanged as they are not affected by this criterion). The number of cells is also reduced, from over five million to 3.34 million, as in some local labour market hirings take place in the first half of the year only. Specifically, the number of cells falls . Overall, despite halving the time window adopted for the consideration of new hires, the degree of concentration does not increase by a similar magnitude. More important, the average HHI is still significantly below the 2,500 threshold at which concentration has been thought to have an impact on market outcomes; and the percentage of workers in this case only (new hirings) that are subject to HHIs above 2,500 is below 13% (compared to 8.7% in the benchmark case).

A second alternative measure involves the consideration of collective bargaining job titles instead of occupations. Collective bargaining plays an important role in the labour market of Portugal and many other European countries, in some cases because of workers affiliation rates, in others because of the widespread use of administrative extensions of collective agreements (Martins 2019). These extensions, issued by the government, determine that sectoral collective agreements need to be followed by virtually all firms and employees in the relevant industry, even those employees and firms not members of the trade unions or employer associations that conducted the bargaining. In this context, the over 30,000 job titles established in collective agreements (each one of which subject to its time-varying minimum wage) can be interesting alternatives for the classification of workers in terms of their occupations, especially as they are also registered in the 'Quadros de Pessoal' data set that we use. However, these alternative occupation measures are also very likely to overestimate the number of local labour markets and therefore led to spuriously high concentration figures. For instance, a secretary in the metalwork industry will have a different job title code than a secretary in the retail sector even if their jobs are highly substitutable and if they are located in the same district. In other words, the relevance of this measurement approach will depend on the degrees of industry-specific skills or of actual differentiation in individual occupations.

Under this second definition of occupations, we find that the number of labour market cells increases dramatically, from 14,466 to 79,088. This reflects the fact that the occupation codes also increase by a factor or more than 20 as we move from the benchmark case to the collective bargaining job titles.[5] More importantly, we find that our average HHI measures more than double in both cases (employment stocks and flows), reaching 1,780 and 2,011, respectively. The percentage of workers in local labour markets with HHIs above the potentially critical thresholds of 2,500 also more than doubles, reaching nearly 20%, a figure similar to the one found for the U.S. in Azar et al. (2018). Given the potential double-counting of occupations in this approach as described above, we regard this alternative measure as an upper bound of concentration in the case of our study.

Our third alternative from our benchmark measure is based on considering more disaggregated regional definitions ('concelhos' instead of 'districts'). This option is influenced by the findings in Manning & Petrongolo (2017), which present evidence that labour markets can be very local, as jobseekers reduce their search efforts considerably at longer distances. In our case, the 'concelho' level has 15 times more units in total when compared to 'distritos' and are roughly equivalent to U.S. counties. 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 cases. We find, first, that the the number of occupation-region-year cells increases by more than four times from the benchmark case to nearly 60,000, reflecting

[5]The average number of workers and hirings also increases reflecting the fact that the number of missing observations in collective bargaining titles is more limited than under the occupations variable used before.

the far more disaggregated nature of the local labour market - Table 3, fourth row. On the other hand, the HHI measurements also increase, to 1,477 and 1,882, 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 2,500 (17.7% in this case).

Next we examine the role of the large percentage of small firms in the labour market of Portugal as potential driver of the main results above, namely the low HHI levels found so far. As documented in Cabral & Mata (2003) and Braguinsky et al. (2011), Portugal tends to exhibit a different distribution of firm sizes than several other developed countries, with a larger mass at smaller sizes.[6] The prevalence of small firms, while potentially negative in terms of productivity and therefore wages, may also potentially affect the comparability of our measurement of market power in the labour market, by downplaying the role of larger firms in each local labour market.

We examine the issues above by removing from our analysis any firm that employs fewer than ten employees in a given year. Table 3, second row from the end, indicates that, as expected, this restriction leads to a significant decrease of the average number of workers and hirings, to 1.89m and 0.38m, respectively. Moreover, the HHI measurements increase significantly, by more than 40%, both in the cases of employment stocks and flows, to 1,124 and 1,426, respectively, but not as much as in other measurement approaches. This is also reflected in the fact that the percentage of workers under HHI levels above 2,500 in this case is the second lowest across the different approaches in this subsection, at 12.5%. We therefore find that, while the small firm dimension influences, as expected, our result on concentration, it is not a critical factor behind the relatively low concentration measures found in our benchmarking analysis.

Finally, we consider the sectoral dimension. As indicated before, some studies of employer concentration can only examine the manufacturing sector because of data limitations (Benmelech et al. 2018, Rinz 2018, Duan & Martins 2019). In order to shed light on the potential impact of such methodological approach, we restrict our attention to manufacturing sector firms only. The last row of Table 3 presents the results, which indicate significantly

[6]A phenomenon also observed in other (Southern) European countries, this large percentage of small firms may be explained by a number of factors, including restricted access to credit, lower management quality, regulations/tax compliance (making firms less able or keen to grow in order to escape such regulations), and employment law strictness (prompting firms to make greater use of service providers/independent workers instead of formal employees in order to have greater flexibility in hiring and firing (Martins 2009*b*)).

higher levels of concentration, with HHI's of 1,190 and 1,683 (employment stocks and flows, respectively) and an employment share above 2,500 of 13.7%.[7]

In conclusion, by exploiting the richness of our matched employer-employee data, covering the universe of firms and their employees, we find that the measurement of employer concentration is sensitive to different methodological choices. This sensitivity refers to different concepts used when defining not only the occupational and regional dimensions, but also the focus on employment stocks or flows and the potential inclusion or exclusion of smaller firms or particular sectors.

In this Section, all departures from the benchmark case entailed increases in concentration by construction. Other types of changes that could be considered would move the results in the opposite direction. Examples would include more aggregated occupation classifications (four- or three-digit level, instead of the five-digit level considered) or longer time windows in the measurement of hirings. Of course, one could consider instead measurement approaches that would combine some or all of the changes examined here, in particular the first three.All in all, our range of estimates presented here offer a better understanding of the sensitivity of concentration measures to different methodologies. This range can also be particularly useful in comparing estimates from studies that draw on less comprehensive data.

5 Wage effects

It is well know that, 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 levels offered to and eventually accepted by workers. We argue here that, alternatively, high levels of employer concentration, in particular when involving large firms, may lead to the emergence or strengthening of unionisation and collective bargaining.

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

[7] All these measures also hold when considering a constant set of (7,968) local labour markets that are present in all years over the 1995-2009 period and our benchmark parameters. However, concentration drops evens further, by approximately 15% across all years and types of measurement (stocks or flows) - results available upon request. These results indicate that turnover in local labour markets, from the entry and exit of occupation-region cells, typically characterised by fewer workers, tends to increase average concentration levels.

also product market power. Such countervailing, trade-union-based mechanism would lead to a more balanced relationship between the employer and the employee sides, where the wage setting power of the former is attenuated and the rent sharing dimension may even possibly gain greater predominance.[8] 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).

In this context, after establishing the levels of employer concentration across labour markets in the previous Section, we now estimate the impact of such concentration on workers' wages. More specifically, in our benchmark local-labour-market specifications, we estimate the following equation:

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

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 $l(o,d)$ in year t. $\delta_{l(o,d)}$ are fixed effects for each local labour market, ϕ_t are fixed effects for each year, and τ_i are worker 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.[9]

Table 4 presents the first set of results, covering the full 1991-2013 period (and over 47 million individual observations). We consider three specifications: the first controlling only for year fixed effects (ϕ_t), the second controlling as well for occupation fixed effects and district fixed effects, and the third controlling instead for local labour market fixed effects (occupation-district pairs, $\delta_{l(o,d)}$). In all cases we exclude worker fixed effects to obtain estimates equivalent to those derived from pooled worker data. We find in all three specifications significantly positive elasticities, with positive coefficients ranging between 0.018 and 0.045. These results

[8]See Martins (2009*a*) and Card et al. (2018) for evidence of rent sharing in Portugal, based on the same data set used here. As discussed before, collective bargaining is pervasive in Portugal, despite low unionisation rages, given the nearly automatic extension of collective agreements. Collective agreements tend to cover the entire country, therefore reducing the scope for differentiated adjustments at different regions. As to other labour market institutions that may also affect wage determination, the most important include minimum wages and unemployment benefits. While the former were relatively low in Portugal during the period under analysis (particularly until 2006), unemployment benefits were relatively generous, in terms of replacement rates and maximum duration.

[9]Unlike in Azar et al. (2017), we do not consider specifications that control for local labour market tightness as we do not have information on applications for each vacancy.

are 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 through (collective) bargaining.

We find similar positive effects when controlling for worker fixed effects - see Table 5. However, the magnitude of the coefficients drops considerably, now ranging between 0.004 and 0.009 across the three specifications. These results suggest 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.

In contrast to the implicit assumption in the previous analyses, one may argue that concentration measures are not likely to be exogenous with respect to wages. Larger local labour markets (with lower concentration levels) may attract more productive firms that pay higher wages and want to be able to hire workers more quickly, for instance. While we control for time-invariant differences across local labour markets and for economy-wide year effects, 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 and lower wages in the resulting jobs, 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 case of Portugal following its China shock (Cabral et al. 2018) as well as possibly more concentrated employment in specific occupations, as some firms exit the market.

We address this issue by developing an instrumental variable for $HHI_{l(o,d),t}$, following Azar et al. (2017) and earlier research in industrial organisation and labour economics. Our instrument for HHI 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 6 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, we find again significant positive effects but only when not controlling for local labour market fixed effects. In our specifications with such controls, either for occupations and districts separately (column 2) or for occupation-district pairs (column 3), we find again positive wage effects, but of less than 1% (0.001 and 0.007).Given the interquartile range of nearly 900 HHI points presented in Section 2 and its resulting difference in logs of 2.33 points, we estimate that workers that would move from low- to high-concentration local labour markets (defined here as percentiles 25th and 75th, respectively) would experience an increase in wages of approximately 0.2%.[10]

Finally, we examine the role of firms in wages and their potential confounding effect in studies of of employer labour-market power. As discussed above, highly-concentrated labour markets may derive their concentration levels 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. In this last robustness check, we add firm fixed effects to our equation to control for the forces above. Identification of firm and worker effects is based on mobility of workers across firms over time. While we are not able to separately identify region from firm effects, as firms are virtually always present in the same region over time, we can estimate local labour market effects as we have multiple firms and workers in each occupation-district pair.

[10] We conduct a number of robustness checks around these. In the first case, we consider an alternative measure of employer concentration, the HHI based on employment flows (and not stocks as before). Given that this measure may be more directly linked to the specific situation in the labour market in each year, this may better reflect the opportunities for wage growth of incumbent workers, for instance in terms of mobility to other firms. On the other hand, wages can be subject to downward nominal wage rigidity implying that even a difficult situation in the local labour market, with limited and highly concentrated new vacancies, may not translate into significant wage cuts or significantly lower wage growth. The results, presented in Table A1, indicate that the two types of mechanisms with opposite effects described here appear to cancel out. The estimates are virtually equal, only marginally smaller, when compared to those obtained under the HHI measure obtained from employment stocks. An additional advantage of this equation is that it may be the closest to the benchmark results in Azar et al. (2017), which find much higher elasticities of between -0.116 and -0.2.

Our second robustness test involves the analysis of potential nonlinearities in these effects. For instance, the small wage effects that we have obtained so far may reflect the fact that most of our HHI distribution is at relatively low concentration levels. These wage effects may be considerably higher at higher HHI levels. We approach this question by restricting our analysis to the top 25% of the HHI distribution in our sample. However, as presented in Table A2, we find again very similar and very small elasticities. Only when using base instead of total wages as our dependent variable (Table A3) we find negative elasticities, of around -0.016.

Table 7 presents the results of this more comprehensive specification, in which we find negative elasticities, of -0.014 and -0.016. 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 presented above of 2.33 log points, 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 4%.

6 Conclusions

Exploiting rich matched data for Portugal, we made a number of contributions to the literature on labour market monopsony. In particular, we present evidence of the significance of employer labour-market concentration, in terms of its magnitude and wage effects. First, we find that at least 9% of workers can be regarded to be exposed to concentration levels thought to raise market power concerns, a percentage that has remained relatively stable over the 20-year period covered. Second, we estimate wage-concentration elasticities that are significantly negative, ranging between -1.5% and -3%, implying that workers that would move from between the bottom and top quartiles of the concentration distribution could see their wages fall by between 3% and 7%.

The latter result suggests that employer market power is an important but not necessarily major driver of wage inequality. The smaller elasticities that we document here, when compared to the case of the U.S., may follow from the different labour market 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 other European countries but largely inexistent in the U.S.

From a methodological perspective, our findings highlight the sensitivity of concentration measures with respect to different choices or data 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 that may be more appropriate to address monopsony.

Finally, our results also underline the importance of taking into account both the worker and the firm heterogeneity dimensions when estimating wage-concentration elasticities. High-concentration labour markets may feature 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 potentially bias towards zero any existing negative effects of concentration on wages.

References

Autor, D., Dorn, D., Katz, L. F., Patterson, C. & Van Reenen, J. (2017), The fall of the labor share and the rise of superstar firms, NBER Working Paper 23396.

Azar, J. A., Marinescu, I., Steinbaum, M. I. & Taska, B. (2018), Concentration in us labor markets: Evidence from online vacancy data, NBER Working Paper 24395.

Azar, J., Marinescu, I. & Steinbaum, M. I. (2017), Labor Market Concentration, NBER Working Paper 24147.

Benmelech, E., Bergman, N. K. & Kim, H. (2018), Strong Employers and Weak Employees: How Does Employer Concentration Affect Wages?, CARRA Working Paper 2018-15, Center for Economic Studies, U.S. Census Bureau.

Braguinsky, S., Branstetter, L. G. & Regateiro, A. (2011), The Incredible Shrinking Portuguese Firm, NBER Working Paper 17265.

Cabral, L. M. B. & Mata, J. (2003), 'On the Evolution of the Firm Size Distribution: Facts and Theory', *American Economic Review* **93**(4), 1075–1090.

Cabral, S., Martins, P. S., Pereira dos Santos, J. & Tavares, M. (2018), Collateral Damage? Labour Market Effects of Competing with China at Home and Abroad, IZA Discussion Paper 11790.

Card, D., Cardoso, A. R., Heining, J. & Kline, P. (2018), 'Firms and Labor Market Inequality: Evidence and Some Theory', *Journal of Labor Economics* **36**(S1), 13–70.

DoJ/FTC (2010), Horizontal merger guidelines, U.s. department of justice and the federal trade commission.

Duan, W. & Martins, P. S. (2019), Rent sharing in China: Magnitude, Heterogeneity and Drivers, IZA Discussion Paper 12169.

Falch, T. (2010), 'The Elasticity of Labor Supply at the Establishment Level', *Journal of Labor Economics* **28**(2), 237–266.

Figueiredo, O., Guimaraes, P. & Woodward, D. (2014), 'Firm-worker matching in industrial clusters', *Journal of Economic Geography* **14**(1), 1–19.

Krueger, A. B. & Ashenfelter, O. (2018), Theory and evidence on employer collusion in the franchise sector, NBER Working Paper 24831.

Manning, A. (2010), 'The plant size-place effect: agglomeration and monopsony in labour markets', *Journal of Economic Geography* **10**(5), 717–744.

Manning, A. (2011), *Imperfect Competition in the Labor Market*, Vol. 4 of *Handbook of Labor Economics*, Elsevier, chapter 11, pp. 973–1041.

Manning, A. & Petrongolo, B. (2017), 'How Local Are Labor Markets? Evidence from a Spatial Job Search Model', *American Economic Review* **107**(10), 2877–2907.

Martins, P. (2009*a*), 'Rent sharing before and after the wage bill', *Applied Economics* **41**(17), 2133–2151.

Martins, P. S. (2009*b*), 'Dismissals for Cause: The Difference That Just Eight Paragraphs Can Make', *Journal of Labor Economics* **27**(2), 257–279.

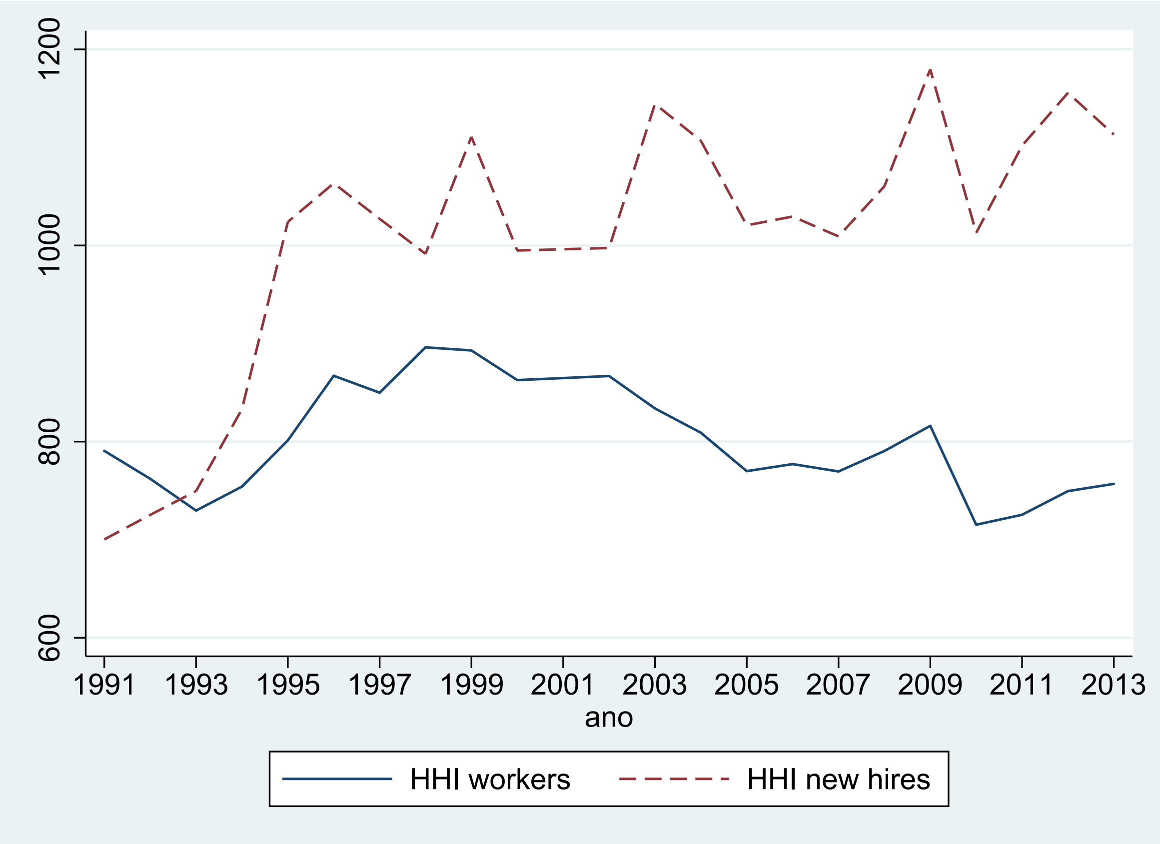
Martins, P. S. (2019), 30,000 Minimum Wages: The Economic Effects of Collective Bargaining Extensions, GLO Discussion Paper 413.

Matsudaira, J. D. (2014), 'Monopsony in the Low-Wage Labor Market? Evidence from Minimum Nurse Staffing Regulations', *Review of Economics and Statistics* **96**(1), 92–102.

Rinz, K. (2018), Labor Market Concentration, Earnings Inequality, and Earnings Mobility, CARRA Working Paper 2018-10, Center for Economic Studies, U.S. Census Bureau.

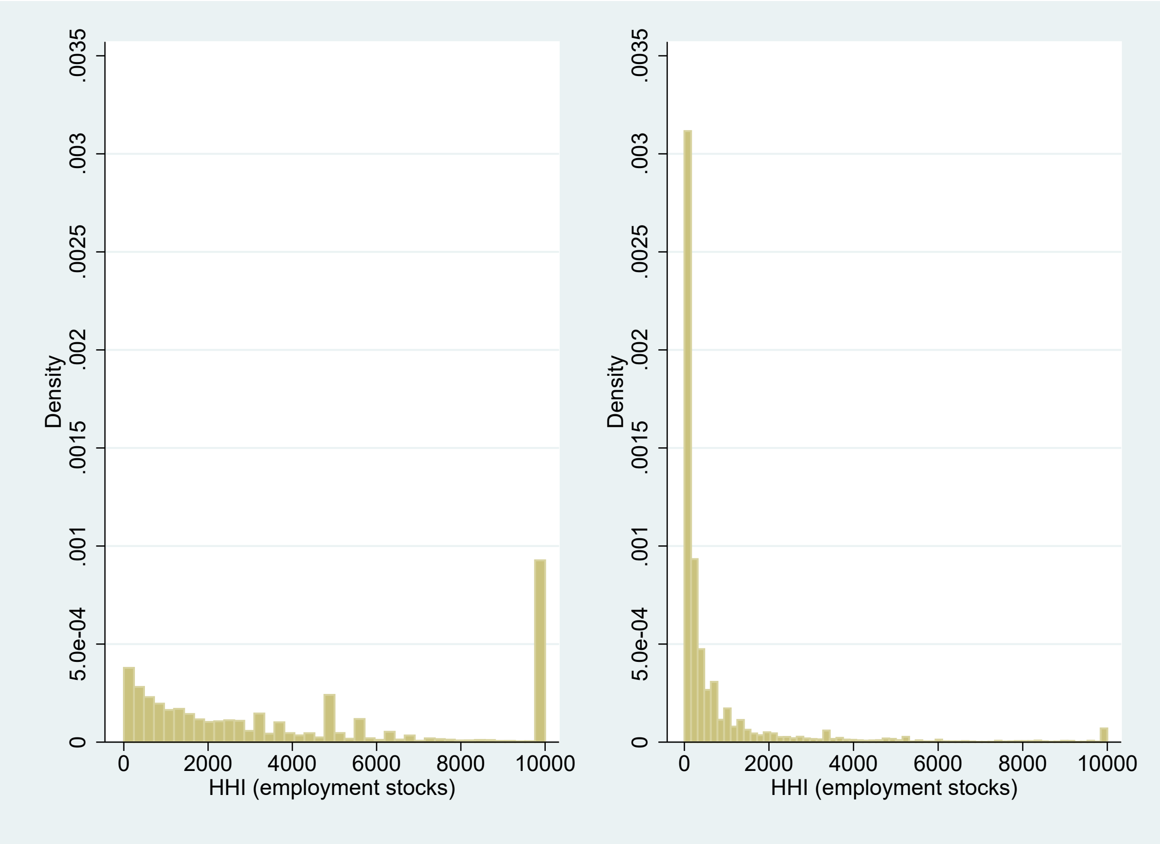
Staiger, D. O., Spetz, J. & Phibbs, C. S. (2010), 'Is There Monopsony in the Labor Market? Evidence from a Natural Experiment', *Journal of Labor Economics* **28**(2), 211–236.

Figure 1: **HHI by number of employees and of new hires (weighted), 1991-2013**



Notes: Own calculations based on the 'Quadros de Pessoal' data set. See the Herfindhal index formula in equation 1 and Table 1 for more details on each time series. Figures for 2001 are interpolated 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. 'HHI works' corresponds to employment stocks; 'HHI new hires' corresponds to employment flows (workers employed in October of each year (March in 199193) and hired over the previous 12 months).

Figure 2: **Distribution of HHI by number of employees across local labour markets (left: unweighted; right: employment-weighted), 2006**



Notes: Own calculations based on the 'Quadros de Pessoal' data set. See the Herfindhal formula in equation 1. Left-hand-side distribution: All local labour markets (occupation-district pairs) carry the same weight, regardless of the number of workers. Right-hand-side distribution: Each local labour markets (occupation-district pairs) carries a weight in the histogram that is proportional to its employment level.

Table 1: **HHI values (weighted), 1991-2013**

Year	HHI (workers)	HHI (hirings)	N. cells	N. workers	N. hirings
1991	790.6	700.3	10237	1963350	398971
1992	762.2	725.3	10211	1986647	380778
1993	729.7	749.6	10352	1980966	349980
1994	754.2	833.2	10469	1927961	321426
1995	801.3	1024.1	12413	1993603	339957
1996	867.2	1063.4	12272	1968477	346704
1997	849.9	1027.2	12657	2150737	438352
1998	896.1	991.5	13717	2185320	454425
1999	893.0	1110.8	15066	2283315	449316
2000	862.7	994.9	15721	2494350	552783
2002	866.9	997.4	17556	2695196	584535
2003	833.9	1144.4	18595	2800003	540625
2004	809.1	1106.8	19178	2891959	569950
2005	769.9	1020.6	19640	3065839	630755
2006	777.1	1029.5	19770	3111190	661384
2007	769.6	1009.3	19963	3220102	742339
2008	790.5	1060.4	20107	3267603	763912
2009	816.1	1179.6	19985	3125383	623430
2010	715.3	1013.0	10149	2842842	561172
2011	725.4	1101.8	10119	2797408	525329
2012	749.6	1155.6	10057	2616314	423911
2013	756.9	1113.2	10023	2608058	476152

Notes: See the Herfindhal index formula in equation 1. HHI (workers) denotes the mean Herfindhal index in each year considering the distributions of employees across firms in each district-occupation-year cells. HHI (hirings) denotes the mean Herfindhal index in each year 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. 'N. cells' indicates the number of district-occupation pais in each year. 'N. workers' ('N. hirings') indicates the total number of workers (hirings) in each year. Figures for 2000 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 2: **Descriptive statistics, district-occupation-year cells, 1991-2013**

		Unweighted		Weighted			
Variable	Obs	Mean	Std. Dev.	Mean	Std. Dev.	Min	Max
Year	318,257	2002.6	6.1	2003.0	6.5	1991.0	2013.0
Number of workers	318,257	175.9	1201.7	8386.7	17180.8	1.0	121286.0
Number of new hires	318,257	35.0	276.3	1759.7	3456.8	0.0	21924.0
HHI (n. of workers)	318,257	4204.7	3696.0	797.6	1746.7	1.0	10000.0
HHI (n. of new hires)	318,257	3311.1	3880.1	1055.0	1972.3	0.0	10000.0
Mean base pay	316,391	626.2	605.7	566.2	532.1	0.0	25837.7
Mean total pay	316,391	768.1	914.3	682.6	722.7	0.0	229576.9

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 for each district-occupation-year cell.

Table 3: **HHI mean values, different measurement approaches**

	HHI		Average number of			% workers
Measurement type	Workers	Hirings	cells	workers	hirings	HHI≥2,500
Benchmark case	799.4	1006.9	14466.23	2544392	506190.3	8.7
Hirings (prev 6 months only)	799.4	1169.7	14466.23	2544392	334755.8	12.9
Collective barg job titles	1779.9	2010.5	79078.00	2618743	563196.1	19.9
Less aggregated regions	1476.8	1881.5	59864.77	2544392	534710.6	17.7
Only firms 10+ employees	1123.9	1425.6	12396.18	1892149	382946.4	12.5
Manufacturing sector only	1190.3	1683.6	8653.86	652751	89342.1	13.7

Notes: 'Benchmark' measurement type is the main one adopted in the paper, based on approximately 1,400 occupations and 30 districts. 'Hirings in previous 6 months' is the same approach except that the HHI hirings 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). '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). '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. '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. HHI and number of cells, workers and hirings are unweighted averages of the weighted HHI yearly data, over the 1991-2013 period. The last column indicates the weighted percentage of cells across all years that have HHI levels above 2,500 (workers HHI except the second row, which denotes new hirings HHI).

Table 4: **Wage results, OLS, 1991-2013**

	(1)	(2)	(3)
Log Herfindhal Index	0.045	0.018	0.030
	(0.000)***	(0.000)***	(0.000)***
Constant	8.151	8.297	8.232
	(0.000)***	(0.000)***	(0.001)***
N	47612744	47612704	47609180
adj. R^2	0.929	0.959	0.961
F	666,274	39,873	29,708
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
Occupation x Distrit FE	0	0	1
Firm FEs	0	0	0
Worker FEs	0	0	0

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 2 - and employment levels. '(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. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 5: **Wage results, OLS incl worker fixed effects, 1991-2013**

	(1) Spec 1	(2) Spec 2	(3) Spec 3
Log Herfindhal Index	0.009	0.003	0.004
	(0.000)***	(0.000)***	(0.000)***
Constant	6.683	6.716	6.710
	(0.000)***	(0.001)***	(0.001)***
N	40141430	40141392	40137450
adj. R^2	0.713	0.723	0.726
F	25,205	873.2	713.5
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Firm FEs	0	0	0
Worker FEs	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 2 - and employment levels. '(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. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 6: **Wage results, IV incl worker fixed effects, 1991-2013**

	(1)	(2)
Log Herfindhal Index	0.001	0.007
	(0.000)**	(0.001)***
N	40065142	40061150
adj. R^2	0.725	0.727
F	4.854	37.41
Year FEs	1	1
Occupation FEs	0	0
District FEs	0	0
(Occupation x District) FEs	0	1
Firm FEs	0	0
Worker FEs	1	1
Auxilliary regression (First-stage)		
Log inverse of number of firms	-7.855	-4.489
	(0.022)***	(0.021)***
N	40065142	40061150
adj. R^2	0.910	0.973
F	131,059	46,734
Kleibergen-Paap rk Wald F-stat	131,059	46,734
P-value	0	0
Shea's R2	.1145	.03131

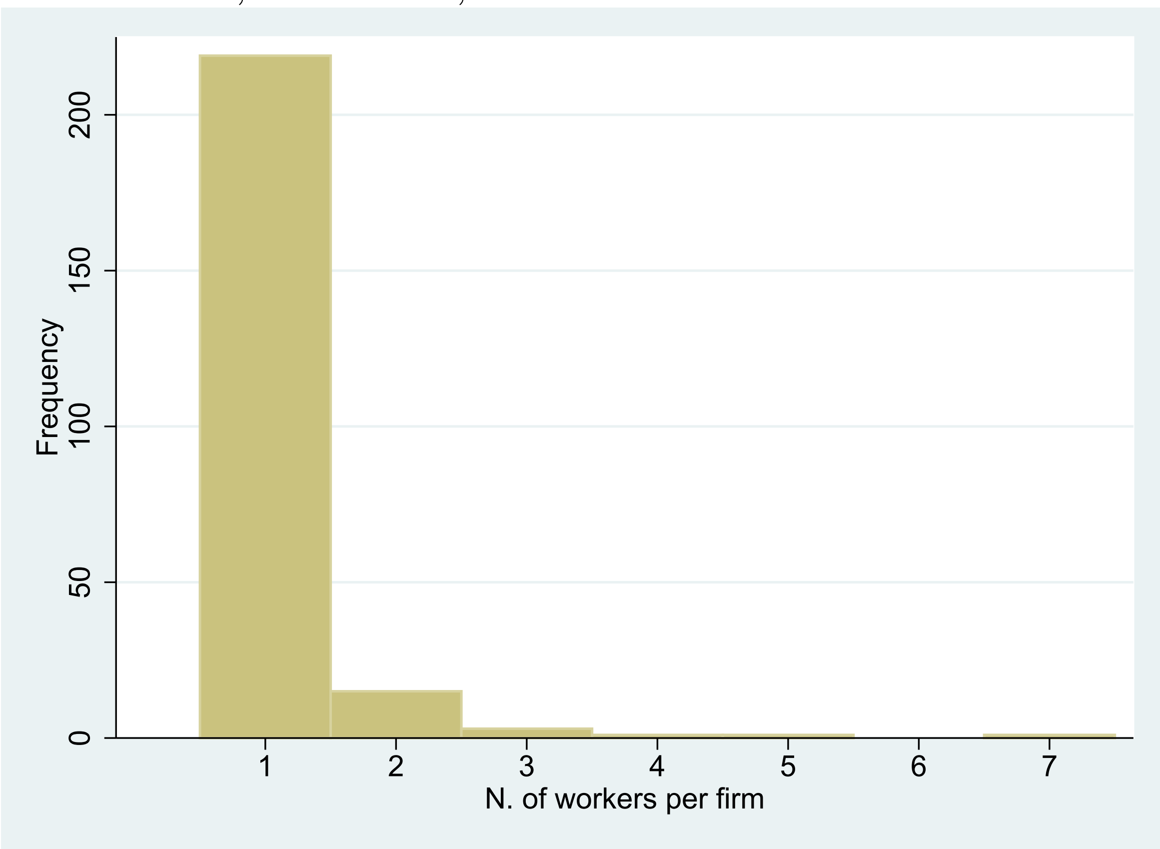
Notes: The columns in the top panel present different specifications of wage equation 2. The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above - see Table 2 - and employment levels. '(Occupation x District) FEs' denote fixed 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. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 7: **Wage results, IV incl worker and firm fixed effects, 1991-2013**

	(1)	(2)	(3)
Log Herfindhal Index	0.013	-0.016	-0.014
	(0.000)***	(0.000)***	(0.000)***
N	39947797	39947781	39943834
adj. R^2	0.758	0.763	0.765
F	15,662	1,068	1,026
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Firm FEs	1	1	1
Worker FEs	1	1	1
Auxilliary regression (First-stage)			
Log inverse of number of firms	0.744	0.561	0.630
	(0.000)***	(0.001)***	(0.000)***
N	39947797	39947781	39943834
adj. R^2	0.847	0.903	0.959
F	13,759,899	891,624	1,654,358
Kleibergen-Paap rk Wald F-stat	13,759,899	891,624	1,654,358
P-value	0	0	0
Shea's R2	.4616	.0464	.124

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 2 - and employment levels. '(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. Significance levels: * 0.10, ** 0.05, *** 0.01.

Figure A1: **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 A1: **Wage results, IV incl worker fixed effects, new hirings HHI measure, 1991-2013**

	(1)	(2)	(3)
Log Herfindhal Index	0.027	0.002	0.001
(new hires measurement)	(0.000)***	(0.000)***	(0.000)***
N	39534202	39534165	39530612
adj. R^2	0.711	0.721	0.724
F	67,535	10.08	10.81
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Firm FEs	0	0	0
Worker FEs	1	1	1
Auxilliary regression (First-stage)			
Log inverse of number of firms	0.744	0.587	0.665
	(0.000)***	(0.001)***	(0.000)***
adj. R^2	0.775	0.844	0.917
F	16,707,191	971,410	1,791,498
Kleibergen-Paap rk Wald F-stat	16,707,191	971,410	1,791,498
P-value	0	0	0
Shea's R2	.4554	.03925	.08688

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 2 - but considering new hirings (12 months) and not employment levels. '(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. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table A2: **Wage results, IV incl worker fixed effects, subset of high HHI levels, 1991-2013**

	(1)	(2)	(3)
Log Herfindhal Index	0.037	0.012	0.008
	(0.001)***	(0.002)***	(0.002)***
N	10310899	10310874	10306658
adj. R^2	0.763	0.770	0.775
F	3,715	46.57	27.71
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Firm FEs	0	0	0
Worker FEs	1	1	1
Auxilliary regression (First-stage)			
Log inverse of number of firms	0.375	0.287	0.353
	(0.000)***	(0.001)***	(0.001)***
Auxilliary regression (First-stage)			
N	10310899	10310874	10306658
adj. R^2	0.719	0.805	0.905
F	1,050,095	142,807	288,326
Kleibergen-Paap rk Wald F-stat	1,050,095	142,807	288,326
P-value	0	0	0
Shea's R2	.2163	.02927	.07346

Notes: The columns in the top panel present different specifications of wage equation 2. Only observations corresponding to the top 25% HHI (employees) levels. The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above - see Table 2 - and employment levels. '(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. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table A3: **Wage results, IV incl worker fixed effects, base wages, 1991-2006**

	(1)	(2)	(3)
Log Herfindhal Index	0.021	-0.017	-0.016
	(0.000)***	(0.000)***	(0.000)***
N	40042347	40042331	40038412
adj. R^2	0.737	0.747	0.749
F	50,221	1,529	1,619
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Firm FEs	0	0	0
Worker FEs	1	1	1
Auxilliary regression (First-stage)			
Log inverse of number of firms	0.755	0.563	0.645
	(0.000)***	(0.001)***	(0.000)***
N	40042347	40042331	40038412
adj. R^2	0.794	0.879	0.956
F	15,554,065	872,536	1,818,794
Kleibergen-Paap rk Wald F-stat	15,554,065	872,536	1,818,794
P-value	0	0	0
Shea's R2	.4526	.04064	.1295

Notes: The columns in the top panel present different specifications of wage equation 2. The dependent variable is the log of individual base wage (not total wage as before). The Herfindhal index corresponds to the benchmark model presented above - see Table 2 - and employment levels. '(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. Significance levels: * 0.10, ** 0.05, *** 0.01.