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Concentration and mergers: evidence from Italian labor markets

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Abstract

This article investigates the effects of labor market concentration on employment, job security, and wages. By constructing a flow-based index, I find that concentration is generally low across markets but varies across industries. Then, I use a Two-Stage Least Squares (TSLS) strategy based on the different exposures of industries to horizontal mergers. I find that mergers increase concentration, which in turn reduces wages by −0.14 and −0.07 and hires by −0.77 and −0.68%age points. I also find that (1) concentration does not affect the likelihood of a permanent hire but increases the probability that, when a temporary worker is renewed, the contract is again temporary; (2) men are affected by concentration only through wages, while women are less affected but also through job security; (3) estimates magnitude increases in concentration levels.

Keywords: monopsony; labor market concentration; mergers; job security; wages; hires
JEL classifications: J31, J42, J71, L13, L41

1. Introduction

Monopsony indicates a case in which a small number of buyers dominate a specific upstream market and, to maximize profits, fix input purchases and prices below the level that maximizes social welfare (Manning 2003). It may also arise in the labor market and affect many outcomes (Manning 2011). Paker, Stephenson, and Wallis (2023) say "*there is nowadays a need to look beyond models of perfect competition to understand wage determination in early modern labor markets*". Similarly, Card (2022) says "*many or even most firms have some wage-setting power*", while Deb et al. (2022) find that monopsonistic dynamics can explain one-quarter of wage stagnation in the United States in recent decades.

The literature has mainly estimated monopsony with the labor supply elasticity of workers to firms. The former find that positive elasticities imply that labor supply increases with wages and vice versa, indicating the presence of monopsony power (e.g. Amodio and de Roux 2021; Langella and Manning 2021; Sokolova and Sorensen 2021; Card 2022; Datta 2023). More recently, labor market concentration has been identified as a proxy of monopsony (e.g. Arnold 2021; Azkarate-Askasua and Zerecero 2023; Bassanini, Batut, and Caroli 2023; Dodini et al. 2023; Bassanini et al. 2024), especially in the presence of workers' limited bargaining power and relevant labor market frictions (Amodio, Medina, and Morlacco 2022; Boeri, Garnero, and Luisetto 2023).

Theory predicts that when concentration increases, wages and employment should fall (Azar, Marinescu, and Steinbaum 2019; Manning 2021).[1] Recently, a stream of this literature has started to revise the labor economics literature in light of monopsonistic competition. Wage inequality (Mertens 2021), gender wage gap (Fanfani 2022; Dodini et al. 2023), workers' misallocation (Lamadon, Mogstad, and Setzler 2022), migration dynamics (Manning 2021), and minimum wage (Popp 2023; Azar et al. 2024) have been studied. However, what drives concentration and what all the effects remain largely unknown.

In this article, I estimate the effect of monopsony, proxied through labor market concentration, on wages, employment, and job security, implementing a novel identification strategy. Italy is the perfect scenario to address job security in particular, as, in the last decades, different reforms have been implemented to reduce firing costs for larger firms.[2] Araki et al. (2023) indeed find that although European labor markets have stronger institutions than the United States, they are not necessarily more competitive, while Luccioletti (2022) finds that a large share of the city-size wage and employment gap between small and large cities in Spain can be attributed to differences in labor market power exerted by firms across locations. The same might apply to the Italian context.

Furthermore, if for wages and employment there is already evidence in the literature, job security has been instead mostly overlooked in all its dimensions while it may represent a relevant channel through which firms exert their dominant position over workers. This article is among the first to address the effect of concentration on different dimensions of job security for new hires and renewals workers, contributing to the emerging literature on monopsony addressing these outcomes (e.g. Bachmann, Demir, and Frings 2022; Amodio, Medina, and Morlacco 2022; Bassanini et al. 2024).

Most of this literature addresses endogeneity through a leave-one-out instrumental variable regression, in which each market concentration index is instrumented with the mean of other indexes in different areas within the same industry or occupation.[3] Only a few papers investigate different channels. Dodini et al. (2023) leverage clusters of skills demanded by firms, Schubert, Stansbury, and Taska (2024) exploit differential local exposure to national firm-level trends, while Datta (2024) emphasizes the role of the spatial distribution of activity and the distaste of workers for commuting.

Recently, a stream of literature has increasingly turned its attention to antitrust issues in light of monopsonistic competition. A growing number of researchers call for more stringent antitrust enforcement, especially regarding horizontal mergers, which are identified as a driving factor for monopsonistic dynamics (Suresh, Eric, and Glen 2018; Shapiro 2019; Posner and Marinescu 2020; Berger et al. 2023; Jarosch, Nimczik, and Sorkin 2024). These scholars argue that the US product markets have become more concentrated in recent decades due to weak merger laws enforced by antitrust agencies. Recently, labor markets have also been scrutinized (Berger et al. 2023; Cali and Presidente 2023). This debate is drawing attention in Europe, but empirical evidence is scarce. I leverage the heterogeneity of labor markets to horizontal mergers to set up a quasi-experiment, additionally contributing as I am among the first to provide causal evidence on this topic.

To my knowledge, only two previous studies used mergers to identify concentration variations in reduced form (Arnold 2021; Guanziroli 2022). However, Guanziroli (2022) focuses on a specific event, and neither explores all the mechanisms and outcomes as I do. Moreover, only two studies have addressed monopsony in Italy (Sulis 2011; Fanfani 2022) while only one labor market concentration (Bassanini et al. 2024), although not specifically in Italy.

[1] More details in Supplementary Section A.

[2] More details in Supplementary Section B.

[3] The aim is to capture national-industry or occupational shocks, ruling out the endogeneity induced by local labor market-specific confounders.

Firstly, I compute concentration across Italian labor markets (LMs) using the Herfindahl–Hirschman Index (HHI). I select only entrant workers' spells–a flow measure–from *LoSaI*, a matched employer–employee dataset drawn from *INPS* (Italian Social Security Agency) between 2005 and 2018. I use a flow-based concentration index rather than a standard stock-based one because it provides a more precise and dynamic picture of how concentration evolves if new hires accurately measure the available job opportunities for workers (Azar et al. 2020; Marinescu, Ouss, and Pape 2021).

Markets are defined as interactions between regions, industries, and job titles. The definition slightly differs from the standard one in the literature, which usually defines a market as an interaction between a commuting zone and an occupation or industry. We use this novel definition to (1) obtain a more" granular" index; and (2) investigate industry heterogeneity in monopsonistic dynamics (Fanfani 2022) as mergers are intrinsically heterogeneous across industries. Most of the 5,008 labor markets identified are not concentrated, as the median value is below the low concentration threshold, and only 3 per cent of workers are exposed to non-low concentration levels according to the US antitrust agency.

I then exploit the *Zephyr* archive to observe horizontal mergers across industries in Italy. I link labor markets and mergers by industry and year and set up a quasi-experimental framework where markets are treated in a year if they experience at least a merger. Mergers do not randomly target markets and are positively correlated with concentration over time. However, industry-level variations are presumably orthogonal to market-specific confounders that affect both outcomes and concentration and bias the estimates toward zero. This allows to identify unbiased effects of concentration on the outcomes.

TSLS estimates show that in treated markets concentration increases by 15–21 percentage points (p.p.), which in turn reduces daily wages by approximately 0.09–0.14 and hires by 0.7–0.8 p.p. The wage effect is entirely driven by the intensive margin (remuneration), while the extensive margin (worked days) is unaffected. I then address job security, measured as the likelihood (1) of being hired with an open-ended contract (OE) and (2) that, when a temporary worker is renewed, the new contract is also temporary. Overall, I find a null effect on permanent hires (Bassanini et al. 2024) but a positive one on temporary transitions. Renewal wages are also negatively affected, although less than new hires' ones and close to the magnitude estimated in Bassanini, Batut, and Caroli (2023) for incumbents.

Results indicate that employers reduce hires and job stability while leveraging temporary renewals to submit workers to a screening period that secures the chance of dismissals. Simultaneously, they compress wages regardless of job security. Additionally, estimates exhibit relevant heterogeneities: wages are more strongly affected for men but precisely estimated for women only, while job security is affected for women only. This suggests that firms exert their power over men and women through different channels. Furthermore, magnitudes, regardless of the outcome and the workers, increase in concentration levels.

To conclude, this article makes three main contributions: (1) implements a novel identification exploring different channels; (2) delves into how firms jointly leverage wages and job security to secure their dominant position over workers; and (3) investigates unexplored concerns in Europe on the effects of mergers on the labor market suggesting that more stringent and evidence-based antitrust enforcement might be necessary. The rest of the paper is structured as follows: Section 2 describes the data and labor market concentration; Section 3 presents the empirical strategy; Sections 3.3 and 4 present the identification and the estimates, while Sections 4.3 and 4.4 contain additional analysis. Section 5 concludes.

2. Data and concentration

2.1 LoSaI

LoSaI is a longitudinal sample of workers extracted from the *INPS* universe based on their birth date that covers the period from 1985 to 2018. For each worker, approximately 7 per

cent of the Italian private sector, the sample contains all his working spells. For each one, it provides the gross overall remuneration, the days and weeks worked, the job title (employees, managers, middle managers, apprentices, and standard workers), the type of contract, the time schedule, and the region of residence. It also provides a unique firm code that can be matched with a firm dataset to obtain a matched employer–employee dataset. This dataset provides the industry (two-digit), and the size class, which varies over time and is classified into 14 brackets from 1–5 to over 500 employees (Supplementary Section C.1).

I select only new hires between 2005 and 2018.[4] Although incumbents are also affected by concentration (Bassanini, Batut, and Caroli 2023),[5] theoretical predictions and empirical evidence suggest that employers' power compresses entrants' wages more than long-term incumbents, who are more experienced and protected by stronger legislation (Bassanini et al. 2024). New hires are defined as the spells activated for each individual in a given year in which the firm does not match the one for which the same individual worked in the previous year. Transformations are kept separate for the job security analysis (Section 4.4). I delete repeated observations for each worker-year keeping the longest spell and obtaining an unbalanced worker-level panel made of 3,573,677 newly activated contracts and 1,400,000 entrant workers (Supplementary Table C.1.2).

2.2 Herfindahl–Hirschman index

A labor market is defined as an interaction between an industry s, a job title o, and a region r. The measure of labor market concentration is the standard one in the literature, the HHI, whose formula is:

$$\mathrm{HHI}_{m,t} = \sum_{i=1}^{N_m} s_{imt}^2 \tag{1}$$

where N_m is the total number of firms within the market m and s_{im} is the labor market share of the firm i in market m at time t, defined as the number of hires of the firms in that market in t divided by total hires of all firms belonging to the same market in t. However, *LoSaI* follows workers' careers, and firms' population is presumably not representative. I cannot rely on firms' shares and the HHI as in Equation (1). However, firms' distribution within and across class sizes is similar to that of Italy (Supplementary Table C.1.1). Therefore, I calculate the concentration by modifying the previous formula:

$$\mathrm{HHI}_{m,t} = \sum_{N_{dm}} K_{d,t}^2 \tag{2}$$

where N_{dm} represents the number of size bins in each market m and k is the ratio of the number of new hires for the representative firm in class d, market m, and year t to the total number of hires in m and t. The representative firm's hires for each size class are computed by dividing the number of hires for each year within that size class by the number of firms hiring in the same year within that size class. The idea underlying the construction of this index is that firms within the same class size pay similar wages and that market concentration depends on the heterogeneity of hires across firms' sizes within a labor market. The fact that larger firms or plants pay higher wages is widely documented in the literature (e.g. Bertola and Garibaldi 2001).

The slightly different HHI definition is due to the data features, as *LoSaI* does not cover the universe of firms, but rather a sample extracted on the worker's side. Hence, if I focus

[4] Spells whose worker did not work within the same firm in the previous year.

[5] They find that, in the French labor market, incumbents are affected by concentration with a magnitude that is from two-thirds to three-quarters of that of new hires.

on the sample of available firms, it would yield a sampling bias as firms' inclusion depends on their size. Hence, a firm's share HHI might be biased upward as it is more likely to include larger than smaller firms. However, I find that the class size HHI differs little from the firm's share HHI (Supplementary Fig. C.2.2). I discuss in detail my index in Supplementary Section C.2.

2.3 Descriptive evidence

I compute concentration for approximately 6,000 labor markets. I delete market-year tuples with one spell only.[6] I obtain an almost perfectly balanced panel of 47,727 market-year tuples and 5,008 markets in Italy between 2005 and 2018. I describe concentration across labor markets in Supplementary Table C.1.6 and Supplementary Fig. C.1.1.a, and between industries and regions in Supplementary Figs C.1.2 and C.1.3. On average, concentration across Italian labor markets is mild: the median value is much lower than the threshold defined by the US antitrust agency, 0.15, and only a few markets are concentrated. However, the average is 0.14, indicating a mild concentration. Supplementary Fig. C.1.1a indicates that the distribution is right-skewed: Most of the markets are not concentrated, while a few are.

As a robustness exercise, I compute the HHI distribution on the worker-level panel. Substantially, I weight the HHI by its size, the number of spells, thus removing the potential bias induced by those markets with fewer spells and therefore mechanically higher HHI. Results are displayed in Supplementary Fig. C.1.1b and indicate that, when each market is weighted by the number of spells, the levels of concentration sharply decrease and so do the spikes. This confirms that the spikes are not a concern, and that on average concentration levels in Italy are low. Martins and Melo (2024) find that approximately 9 per cent of Portuguese workers are subjected to non-low concentration levels. Moreover, since they rely on a stock-based index, he probably underestimates the true level of concentration across LMs. In the Italian case, according to my estimates, the percentage is lower, as the median value in the market distribution is 0.05 points. I find that approximately 95,000 spells over more than 3,500,000 entrants' spells occur in markets with an HHI higher than 0.15. They represent approximately 3 per cent; a low share that should not be of concern.

When computing concentration between regions, industries, and job titles separately, concentration increases (Supplementary Tables C.1.6 and C.1.2). Although the distributions tend to shift toward normality, concentration largely differs across industries. My findings are consistent with those of Fanfani (2022), who finds that industry heterogeneity in monopsonistic dynamics explains a relevant portion of the gender wage gap. Concentration could vary over time, peaking during periods of recession, and thus exacerbating the damages of financial shocks on workers. Financial turmoil can amplify labor market volatility (Boeri, Garibaldi, and Moen 2013; Autor, David, and Hanson 2016) and reduce the access of firms to credit markets, which in turn reduces employment (Berton et al. 2018). However, Supplementary Figs C.1.3 and C.1.4 suggest that concentration does not change over time even during the peak of the financial crisis.

3. Empirical strategy

3.1 Wages

I compute daily wages by dividing the total gross remuneration of each employment contract by the number of days worked, thus ruling out the presence of any measurement error. The number of records with a value of 0 for wages is less than 50,000 and, since they

[6] With only one spell the index, for a mechanical bias of the HHI formula in Equation (1), is equal to 1.

likely represent a measurement error, they are dropped. To identify the correlation between concentration and entrants' wages, I estimate the following equation:

$$log(Y_{i,m,t}) = \delta_i + \mu_m + \gamma_s + \Gamma_{r,t} + \Lambda_{d,t} + \Phi_{o,t} + \beta_t + \theta log(HHI_{m,t}) + \Gamma Z_{i,t} + \nu_{i,m,t} \quad (3)$$

where i indexes workers, r regions, o job titles, j firms, d class sizes, s industries, and t years. $Y_{i,m,t}$ is the gross daily remuneration of worker i in market m and year t. Z contains worker-level covariates as a quadratic polynomial for age and spell length to proxy individual-specific working experience and on-the-job working experience. Standard errors are clustered at the market-year level, the level at which concentration varies.

The model is a log–log and hence θ should be interpreted as the elasticity of daily wages to concentration. Equation (3) is estimated with OLS. I exploit both cross-sectional and time variation in concentration and wages, controlling for a full set of time-varying covariates at a worker and market level as well as for market and worker fixed effects, to control for all possible confounding factors. I also control for job title-year, region-year, and size-year fixed effects to take into account potential time-varying confounding effects that jointly influence concentration and wages.

This empirical strategy requires that individuals move between employers and labor markets over time. On average in my sample, approximately 60 per cent of the workers change at least one job and approximately the same also share an employer.[7] As the industry depends on the firm where the worker is employed, it also means that the industry changes at least once for more than 50 per cent of the population. Approximately half of the workers also switch at least one size class, suggesting that size-by-year fixed effects can explain a lot of wage heterogeneity. Individuals do not frequently change job titles; 20 per cent did so between 2005 and 2018. However, I control for job title and region-by-year fixed effects to capture regional and occupational-specific trends in wages and concentration.

3.2 Employment

I measure employment as the number of labor contracts signed in a market during a year (Marinescu, Ouss, and Pape 2021), which I denote as $F_{m,t}$, and estimate the following equation:

$$log(F_{m,t}) = \delta_m + \Phi_s + \gamma_{o,t} + \Theta_{r,t} + \beta_t + \theta log(HHI_{m,t}) + \phi X_{m,t} + \nu_{m,t} \quad (4)$$

where m indexes markets, δ and β represent market and year fixed effects and γ, Φ, and Θ are job title-year, industry, and region-year fixed effects. Standard errors are clustered at the market level to allow records belonging to the same market to be correlated across time, as the shocks can be time-persistent within markets. Since it is a log–log specification, θ should be interpreted as the elasticity of employment to labor market concentration. X contains the average age and share of men for each market m in year t to account for feasible differences in composition over time, while I rely on a full set of job title-year, industry, and region-year fixed effects to control for value added and employment specific to each market and year.

Estimates again suffer from endogeneity: in the HHI formula, markets with higher spells tend mechanically to have lower levels of concentration, whereas the opposite holds for markets with fewer spells. This mechanism induces a negative relationship between the two variables, which biases toward zero estimates.[8] To address all of these threats, I need to identify a shock that affects concentration but not the outcomes. This variation should rule

[7] I define these workers "switchers" and I provide evidence on the differences with "non-switchers" in Supplementary Tables C.1.4 and C.1.5.

[8] More details in Supplementary Section D.1.

out the joint effect of any labor demand and offer shocks at the market level influencing concentration and the outcomes contemporaneously. Furthermore, it should also be orthogonal to the mechanism inducing a positive correlation between concentration and wages.

3.3 Identification strategy

To obtain an exogenous variation in concentration, I rely on an instrumental variable strategy exploiting horizontal mergers. The antitrust literature has focused on mergers, while a recent stream has begun investigating the relationship with labor market. Several studies find that mergers increase product market concentration (Affeldt et al. 2021; Benkard, Yurukoglu, and Zhang 2021; Saidi and Streitz 2021). However, growing evidence in the United States and Europe suggests that mergers also affect labor market outcomes (Suresh, Eric, and Glen 2018; Marinescu and Hovenkamp 2019; Posner and Marinescu 2020). Berger et al. (2023) find that mergers decrease employment and wages with greater effects in concentrated markets. Reduced form and structural estimates (Shapiro 2019; Arnold 2021; Guanziroli 2022; Jarosch, Nimczik, and Sorkin 2024) and simulations (Marinescu, Ouss, and Pape 2021) show that horizontal mergers increase labor market concentration. Section D.2 describes the literature extensively.

3.3. 1 Data

I exploit the *Zephyr* database provided by the *Bureau Van Dijk* archive, which contains times series of worldwide rumored, announced, and completed mergers and acquisitions operations of all types (partial or full acquisitions, mergers, etc.) from 1997 to today. I select all completed mergers and acquisitions whose target country is Italy from 2005 to 2018. For a sub-sample of these events, I also have information on the number of workers involved and vendor and acquirer sizes. The final sample contains 5,932 events, associated with 4,237 different acquiring firms and approximately the same number of vendors.[9] On average, approximately 423 events happen per year. I provide further details in Supplementary Section D.3.

I select only *horizontal mergers*, in other words, those operations between firms belonging to the same industry. Since markets are defined across industries, mergers between firms across different industries do not raise concentration and thus are discarded. The final number of events from 2005 to 2018 decreases to 184. *Zephyr* provides many details for each record, such as the targeted industries (up to six digits), the number of employees involved,[10] or whether only certain plants and therefore locations are involved, and the names of the firms. Ideally, one would match these firms with other archives through their names, which can be used to recover the fiscal code with virtually no errors. However, the same information is absent in *LoSaI*, which instead provides a two-digit industry and no fiscal code. Therefore, I can only match mergers with workers' records through the industry associated with each firm and the year, exploiting a national-industry-level shock in mergers.

The underlying idea of the identification strategy is that markets that experience mergers become more concentrated over time. Concentration varies through different channels: An industry-level shock could raise market concentration, as the shock would translate to different extents to all markets associated with that industry. Therefore, I exploit a *national-industry shock* in concentration. There is evidence that industry heterogeneity is a driver of monopsonistic dynamics in Italy (Fanfani 2022). The most targeted industries are *Financial Activities, Information and IT Services Activities, Editorial Activities, Electric and Gas Furniture, Manufacture of Machinery and Equipment*, and *Satellite Telecommunication*

[9] The Italian labor market mergers exposure is weak compared to France and Germany, in which, approximately, the same number of operations occurred in 2014–18 (*Oxford Economics*).

[10] Due to missing data I cannot exploit this variable.

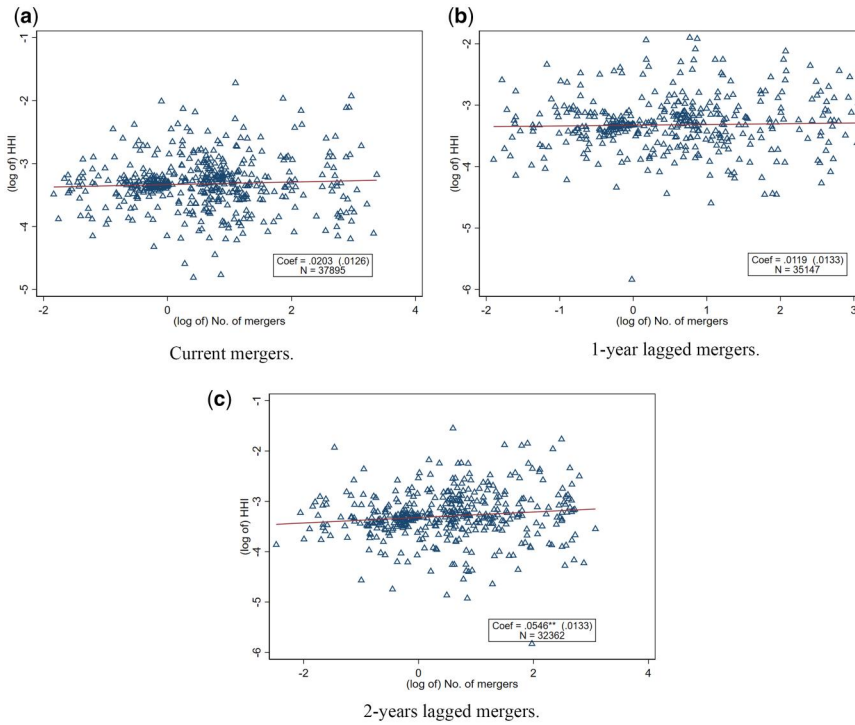

Figure 1. Binscatters between concentration and mergers.

Notes: The lines represent OLS fits of log(HHI) on IHS(mergers); the coefficient is the slope. Market fixed effects are included. Standard errors are clustered at the market level. The sample consists of 48,219 market-year tuples, 4,874 markets, and 184 mergers in 2005–2018. Source: Authors' calculations.

(Supplementary Fig. D.3.1). Figure 1 suggests that the more mergers occur within industries, the more these become concentrated over time.

To the extent that I control for all confounders that jointly influence concentration and mergers, mergers would be a shock in concentration targeting only a subsample of markets and workers,[11] creating a quasi-experimental framework in which mergers are the random treatment affecting concentration. Figure 2 sketches the intuition behind the identification strategy. Relying on mergers in the same market, I would not rule out the direct effect of mergers on wages and hires and the reverse causality triggered by the role of firm-specific characteristics and market-specific confounders. Instead, an industry-national shock affects concentration but does not have a direct effect on the outcomes as income and employment depend on market-specific factors.

I rely on lagged mergers to (1) ensure exogeneity to market-specific dynamics simultaneously influencing mergers and outcomes; (2) incorporate the fact that merged firms need some time to consolidate and display their labor market power. Figure 1 suggests that this is the case, since only the two-year lagged mergers are correlated with concentration.[12] I define two binary (Wald) instruments as:

[11] Consider, for instance, a merger between two competitors at the national level, whose plants are located in one region of Italy. It does not reasonably directly influence workers employed by competitors whose plants are located in different regions.

[12] The estimated elasticity is.055 p.p., which, following an SD increase in the measure of mergers, would yield an increase in HHI of approximately 50 per cent.

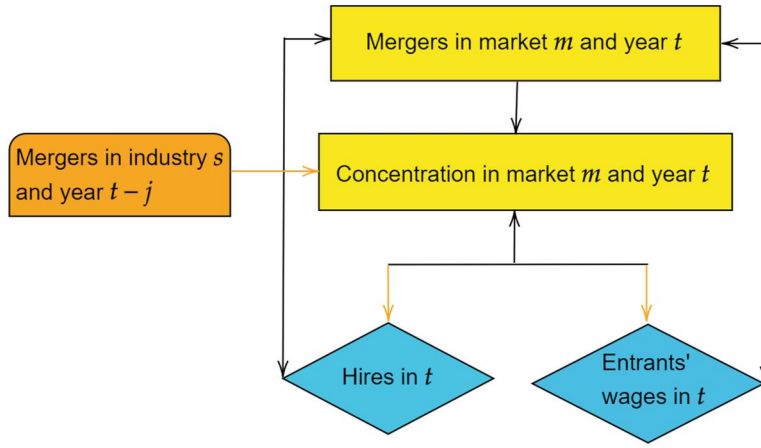

Figure 2. Sketch of the identification strategy.

Notes: The rectangular boxes indicate the endogenous variables, the rounded boxes are exogenous, and the rhomboid boxes indicate the outcomes. The black and orange arrows indicate correlations and causal effects.

$$\mathrm{IV}^1_{m,t} : \forall \mathrm{t} \text{ in } [2005, 2018], \mathrm{I}_{m,t}\{Mergers_{m(s),t-1} > 0\} = 1; \tag{5}$$

$$\mathrm{IV}^2_{m,t} : \forall \mathrm{t} \text{ in } [2005, 2018], \mathrm{I}_{m,t}\{Mergers_{m(s),t-2} > 0\} = 1 \tag{6}$$

where I is a dummy variable equal to 1 if industry s of market $m(s)$ experiences at least one merger in year $t-1$ or $t-2$, 0 otherwise. In other words, I instrument concentration for each labor market and year with a dummy variable indicating whether a market has experiences at least a merger in the previous one or two years. A Wald estimate takes this form:

$$\theta_{IV^k} = \frac{\mathrm{cov}(Y_{i,m,t}, IV^k_{m,t})}{\mathrm{cov}(HHI_{i,m}, IV^k_{m,t})} = \frac{E[Y_{i,m,t} \mid IV^k_{m,t} = 1] - E[Y_{i,m,t} \mid IV^k_{m,t} = 0]}{E[HHI_{i,m} \mid IV^k_{m,t} = 1] - E[HHI_{i,m} \mid IV^k_{m,t} = 0]} \tag{7}$$

which, substituting the expected values with their corresponding averages in the sample, becomes $\hat{\theta}_{IV^k}$ that is, the difference in the average Y between workers belonging to markets that experienced in the past one or two years at least one merger[13] divided by the difference in HHI between treated and untreated markets as predicted by the instrument k. Estimates are Average Treatment Effects on the Treated (ATT) as long as the instruments do not directly affect the outcomes (exogeneity) and are correlated with the endogenous covariate (relevance). I discuss these assumptions and perform a battery of robustness checks in Supplementary Sections D.4 and D.5.

4 Results

4.1 Wages

The results are shown in Table 1. The first panel contains the endogenous estimates. I then display results for the three different specifications: in Panel (a) I use the instrument defined in Equation (5), in (b) the instrument of Equation (6), while in (c) both. Standard errors are clustered at the market-year level, the level at which concentration varies. Estimates indicate that concentration has a sizeable negative impact on entrants' wages. TSLS estimates

[13] The underlying assumption is that the instruments do not directly affect the outcomes, although they affect concentration and in turn the outcomes.

Table 1. OLS and TSLS estimates of Equation (3).

Log (daily wages)	(1)	(2)	(3)	(4)
OLS				
$\hat{\theta}$	0.00209**	−0.00152**	0.00115	−0.0014*
	(0.00075)	(0.00068)	(0.0011)	(0.00081)
TSLS				
(a) $\hat{\theta}_{IV^1}$	−0.319**	−0.114**	−0.1258**	−0.134***
	(0.1354)	(0.0471)	(0.04514)	(0.03803)
(b) $\hat{\theta}_{IV^2}$	−0.282**	−0.0525	−0.0684*	−0.209
	(0.1189)	(0.04419)	(0.0404)	(0.1754)
(c) $\hat{\theta}_{IV^{1,2}}$	−0.300**	−0.0920**	−0.1052**	−0.1393***
	(0.0890)	(0.0326)	(0.0315)	(0.0375)
Observations	2,928,818	2,928,818	2,928,474	2,928,474
quadratic spell length and age	✓	✓	✓	✓
part time dummies	✓	✓	✓	✓
worker FE	✓	✓	✓	✓
year FE	✓	✓	✓	✓
industry FE	–	✓	✓	✓
region FE	–	✓	✓	–
job title FE	–	✓	✓	–
size FE	–	✓	✓	–
market FE	–	–	✓	✓
job title-year FE	–	–	–	✓
size-year FE	–	–	–	✓
region-year FE	–	–	–	✓

Notes: Standard errors clustered at the market-year level in parentheses. Observations are 3,573,677 working spells between 2005 and 2018. $\hat{\theta}_{IV}$ is formally shown in Equation (7). Panels indicate different instruments: (a) 2-year lagged mergers as in Equation (6); (b) 1-year lagged mergers as in Equation (5); and (c) both jointly. Observations are lower than in the full sample and differ across columns because of singletons when including worker and market fixed effects.
Source: Authors' calculations.
*** $P < 0.01$.
** $P < 0.05$.
* $P < 0.1$.

are larger in magnitude than OLS ones, which are close to zero and not significant, because of different labor market level confounders, positively correlated with both concentration and wages, inducing a downward bias. The opposite mechanism is the main threat: the higher concentration, the more there are large, more productive, high-wage firms. This also suggests that the instruments capture exogenous HHI variations.

Magnitude and significance differ across specifications and the Equation (5) instrument is the most significant. Estimates range between −0.14 and 0.068 p.p., while the preferred range between −0.14 and −0.09. It follows that a 10 p.p. increase in market concentration reduces new hires' wages by approximately 0.9–1.4 p.p. Estimates are larger than those of the literature; Marinescu, Ouss, and Pape (2021) reduced form elasticities range between −0.067 and −0.052 points, indicating a reduction in wages following a 10% increase in market HHI of 0.67 and 0.52 p.p., and in general are in line with Card (2022).

Estimates are in line with those obtained in Marinescu, Ouss, and Pape (2021) by simulating a horizontal merger between two top-employing firms, as they find a reduction in a new-firm wage bill of approximately 7 p.p. following a 10-point HHI increase. Arnold (2021) finds elasticities that range between −0.3 and −0.08 p.p., and his findings are quantitatively confirmed by simulating different mergers according to the structural model developed in Berger et al. (2023).[14] Jarosch, Nimczik, and Sorkin (2024) find reduced-form

[14] The authors estimate elasticity ranging between −0.44 and −0.11 p.p.

Table 2. OLS and TSLS estimates of Equation (4).

log(Hires)	(1)	(2)	(3)
OLS			
$\hat{\theta}$	−0.1166***	−0.1167***	−0.0948***
	(0.00445)	(0.00446)	(0.00332)
TSLS			
(a) $\hat{\theta}_{IV^1}$	−0.681**	−0.681**	−0.692**
	(0.2819)	(0.2821)	(0.2867)
(b) $\hat{\theta}_{IV^2}$	−0.771*	−0.771*	−0.747*
	(0.4689)	(0.4694)	(0.4402)
(c) $\hat{\theta}_{IV^{1,2}}$	−0.699**	−0.699**	−0.704**
	(0.2791)	(0.2794)	(0.2792)
Observations	47,180	47,180	47,180
market avg. men share and age	✓	✓	✓
market FE	✓	✓	✓
year FE	✓	✓	✓
job title FE	–	✓	–
region FE	–	✓	–
industry FE	–	✓	✓
region-year FE	–	–	✓
job title-year FE	–	–	✓

Notes: Standard errors clustered at the market level in parentheses. Employment is measured as the number of newly activated working spells within each market and year. Full sample is made up of 47,727 market-year tuples. Columns indicate different sets of fixed effects. $\hat{\theta}_{IV}$ is formally displayed in Equation (7). Panels indicate different instruments: (a) 2-year lagged mergers as in Equation (6); (b) 1-year lagged mergers as in Equation (5); and (c) both jointly.
Source: Authors' calculations.
*** $P < 0.01$.
** $P < 0.05$.
* $P < 0.1$.

elasticities for wages ranging between −0.18 and −0.09 p.p. while, simulating a horizontal merger shifting a market from average to high concentration,[15] they find that wages decrease by 1 p.p.

These values are higher than those estimated on average in the literature and more similar to mine. In summary, my estimates range between those obtained with leave-one-out IVs (Marinescu, Ouss, and Pape 2021; Azkarate-Askasua and Zerecero 2023; Bassanini, Batut, and Caroli 2023; Dodini et al. 2023; Bassanini et al. 2024) and those obtained relying on mergers (Arnold 2021; Marinescu, Ouss, and Pape 2021; Guanziroli 2022; Berger et al. 2023; Jarosch, Nimczik, and Sorkin 2024), and are close to those of Luccioletti (2022).[16]

4.2 Employment

Results are shown in Table 2: the first panel contains the TSLS estimates, while the following contain the OLS ones with the three sets of instruments. TSLS estimates are larger in magnitude than OLS ones, as the different confounders, positively correlated with both concentration and hires, induce a downward bias. TSLS estimates are stable across panels, with elasticities ranging between −0.68 and −0.77 p.p. These elasticities are slightly greater than those estimated by Marinescu, Ouss, and Pape (2021), Arnold (2021), and Luccioletti (2022), which range between −0.31 and −0.585 p.p., −0.9 and −1.4 p.p., and −1.7 and −1.5 p.p. respectively. Results indicate that a 10-point increase in HHI would reduce hires

[15] From the 25^{th} to the 75^{th} percentile in the HHI distribution.
[16] He uses an alternative instrument based on the changes in the local size of the public sector in Spain, estimating elasticities between −0.14 and −0.07 p.p.

by approximately 3–6 p.p. The difference in magnitude might be due to the different framework, identification strategy, or definition of new hires.[17] The more conservative definition of new hires in my framework could explain the higher magnitude of my estimates. Results indicate that when markets move from low to high concentration, hires decline by 7–8 p.p.

4.3 Job security

One of the contributions of this paper is to try to fill a gap in the literature addressing several measures of job security to shed light on how firms exert monopsonistic power over workers. Indeed, Bachmann, Demir, and Frings (2022) find that workers performing non-routinary intellectual tasks are exposed to higher degrees of monopsony than workers performing manual tasks; Amodio, Medina, and Morlacco (2022) find that firms leverage self-employment to overcome workers in monopsonistic frameworks, and Bassanini et al. (2024) that higher concentration reduces the likelihood of being hired with a permanent contract. Furthermore, Italy is the perfect environment to investigate job security, as several reforms have recently been implemented to remove restrictions on temporary employment.[18]

These reforms created a dual labor market where firms could exert their power over workers through job security. They might, for instance, hire temporarily to secure the possibility of dismissals with little cost after a screening period. To avoid looking at the trajectories of workers across different contracts would result in overlooking potential mechanisms through which monopsony power displays. Therefore, I study the likelihood of being hired with an open-ended contract and being renewed, starting from a temporary contract, with another temporary contract. I select as renewal workers those satisfying the following conditions: (1) two consecutive spells in two different years in the same firm; (2) the first is temporary. I obtain approximately 300,000 worker-year records. The empirical specification is shown in Equation (11).

4.3. 1 Permanent hires

Supplementary Fig. D.6.1b displays not statistically significant estimates. I estimate a semi-elasticity of 0.004 with a market-clustered standard error equal to 0.0315 and 0.022 clustered at the market-year level. Overall, concentration does not affect the probability of a permanent hire (Bassanini et al. 2024).

4.3. 2 Renewals

Estimates are shown in Supplementary Table D.6.1. The estimates are statistically significant and positive, indicating that in treated markets the probability of temporary transitions is much higher. The semi-elasticities are approximately 0.48 points, roughly a 60 p.p. increase. Renewals' wages, although not precisely estimated, are negatively affected as well, with a magnitude lower than that of new hires and closer to those of incumbents (≈ -0.08 p.p.). I interpret this as a sign that, in monopsonistic frameworks, employers reduce new hires and their job security while exploiting renewals to extend the screening period and secure future change in dismissals. Simultaneously, they lower both new hires' and renewals' wages.

4.4 Heterogeneity

4.4. 1 Sex

Sulis (2011), Fanfani (2022), Manning (2021), and Dodini et al. (2023) find that monopsony explains gender wage gap in Italy, UK, and Norway. I explore whether and to what extent merger-induced shocks in concentration hurt wages and job security of men and

[17] They define new hires as workers whose spell starts in each quarter, deleting those whose spells start on each January 1.

[18] More details in Supplementary Section B.

women differently. The estimates are shown in Supplementary Fig. D.6.3. Surprisingly, wage estimates are highly significant for women and only marginally men. Men's coefficient becomes marginally significant at 90% confidence level. Although not precisely estimated, men's coefficient drives the magnitude of the baseline estimate upward, as it is approximately ten times that of women (−0.27 vs −0.03 p.p.). There is no effect on job security of men, whereas it is statistically significant at the 90% confidence level and equals −0.03 points for women. A 10 p.p. increase in HHI reduces women's job security by 0.3 p.p.. Overall, men's job security is not affected by monopsony, while their wages are.

4.4. 2 Concentration levels

I split concentration into two brackets: from 0 to 0.15 in HHI, and above it, indicating, respectively, a low versus a not-low concentration level according to the US antitrust agency. Arnold (2021) and Berger et al. (2023) find that mergers have greater detrimental effects on wages and employment in more concentrated markets.[19] The same might apply to job security. Results, additionally split by gender, are shown in Supplementary Fig. D.6.3. From low to high concentrated markets, the elasticity of wages to HHI more than doubles (−0.13 vs −0.3 p.p). For men, although still not precisely estimated, it reaches −0.5 p.p. in highly concentrated markets, while for women, it is precisely estimated and equals −0.1 p.p.

The results on sex and concentration levels shed light on the mechanisms contributing to the gender wage gap in the Italian labor market, as the estimates indicate a striking difference in how monopsony power affects men and women. Furthermore, they also say that the baseline estimates hide a relevant heterogeneity in magnitude and significance and that both concentration levels and shocks are relevant. There is no effect on job security even in highly concentrated markets for men, while the effect is statistically significant and increases in concentration levels for women (−0.03 vs. −0.06 points). In short, concentration (1) damages job security for women only; (2) matters in levels and not only in shocks.

5. Conclusions

This paper investigates concentration and its effects on entrants' wages, job security, and employment by exploiting horizontal mergers as a shock across Italian labor markets. I find that very few new hires occur in markets where concentration is high. I find that mergers raise concentration, which reduces wages and employment. If an average concentrated market becomes 10 points more concentrated, wages and hires decrease by 0.9–1.4 and by 0.7–0.8 percentage points in the following two years, implying a substantial loss of 9–19 euros per month for a full-time worker with an average wage.

In addition, I find that (1) workers subjected to mergers are more likely to undergo consecutive screening periods; (2) men are affected only and largely in the remuneration while women, although with less intensity, also in the security at the hiring stage; and (3) higher concentration levels increase the detrimental effects of concentration variations. These indicate that firms combine the tools at their disposal to exert power over workers and that concentration levels and shocks must be jointly evaluated to identify markets and workers most at risk.

Responsible authorities must therefore be attentive to the labor market spillovers of mergers, in addition to the well-known product market ones, and evaluate mergers on an industry-specific basis, taking into account concentration levels and all outcomes. I believe thus that a stronger enforcement of antitrust laws, data-driven and in specific industries, may be necessary in Italy. In the end, future research should further explore job content and tasks to obtain a full picture of how monopsonistic power displays.

[19] Moving from low to high concentrated markets, Arnold's (2021) elasticity ranges between −0.31 and −0.08 percentage points, while Berger et al.'s (2023) between −0.44 and −0.11.

Supplementary material

Supplementary material is available at the OUP website. This includes the replication files and the online appendix. The data used in this paper, the Longitudinal Sample INPS, LoSaI, are not open access but can be requested freely at INPS compiling an online request detailed at https://www.inps.it/it/it/dati-e-bilanci/File-per-la-ricerca-MFR.html and https://www.inps.it/it/it/dati-e-bilanci/attivit–di-ricerca/file-standard-campionari.html. The full list of databases available in the INPS archive can be seen at the INPS Database Archives and at https://www.inps.it/content/dam/inps-site/pdf/dati-analisi-bilanci/attivita-ricerca/visitinps-scholars/2024/Banche_dati_disponibili_English_version.pdf.

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References

Affeldt, P. *et al.* (2021) 'Market Concentration in Europe: Evidence from Antitrust Markets', CEPR Discussion Paper No. DP15699, London.

Amodio, F., Medina, P., and Morlacco, M. (2022) 'Labor Market Power, Self-Employment, and Development', CEPR Press Discussion Paper 17543, London.

Amodio, F., and de Roux, N. (2021) 'Labor Market Power in Developing Countries: Evidence from Colombian Plants', CEPR Press Discussion Paper 16180, Cambridge, MA.

Araki, S. *et al.* (2023) 'Labor Market Concentration and Competition Policy across the Atlantic', U. Chi. L. Rev. 90, p. 339.

Arnold, D. (2021) 'Mergers and Acquisitions, Local Labor Market Concentration, and Worker Outcomes', Reviewed and resubmitted at the American Economic Review.

Autor, D. H., David, D., and Hanson, G. H. (2016) 'The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade', *Annual Review of Economics*, **8**: 205–40.

Azar, J. *et al.* (2024) 'Minimum Wage Employment Effects and Labour Market Concentration', *Review of Economic Studies*, **91**: 1843–83.

Azar, J., Marinescu, I., and Steinbaum, M. (2019) 'Measuring Labor Market Power Two Ways', AEA Papers and Proceedings 109, pp. 317–21.

Azar, J. *et al.* (2020) 'Concentration in US labor markets: Evidence from online vacancy data', *Labour Economics*, **66**: 101886.

Azkarate-Askasua, M., and Zerecero, M. (2023) 'The Aggregate Effects of Labor Market Concentration'. https://congresscreator.org/system/files/papers/labor_conc_occ.pdf.

Bachmann, R., Demir, G., and Frings, H. (2022) 'Labor Market Polarization, Job Tasks, and Monopsony Power', *Journal of Human Resources*, **57**: s11–s49.

Bassanini, A., Batut, C., and Caroli, E. (2023) 'Labor Market Concentration and Wages: Incumbents versus New Hires', *Labour Economics*, **81**: 102338.
Bassanini, A., Bovini, G., Caroli, E., Casanova, J., Cingano, F., Falco, P., Felgueroso, F., Jansen, M., Ludovice Paixao de Melo, A., Martins, P., Oberfichtner, M., and Popp, M. (2024) 'Labor Market Concentration, Wages and Job Security in Europe', *Journal of Human Resources*, Published online before print March 06, 2024, 0223-12757R1.
Benkard, C. L., Yurukoglu, A., and Zhang, A. L. (2021) 'Concentration in Product Markets', NBER Working Papers 28745. NBER, Cambridge, MA.
Berger, D. W. *et al.* (2023) 'Merger Guidelines for the Labor Market', Working Paper 31147, NBER, Cambridge, MA.
Bertola, G., and Garibaldi, P. (2001) 'Wages and the Size of Firms in Dynamic Matching Models', *Review of Economic Dynamics*, **4**: 335–68.
Berton, F. *et al.* (2018) 'Banks, Firms, and Jobs', *The Review of Financial Studies*, **31**: 2113–56.
Boeri, T., Garibaldi, P., and Moen, E. R. (2013) 'Financial Shocks and Labor: Facts and Theories', *IMF Economic Review*, **61**: 631–63.
Boeri, T., Garnero, A., and Luisetto, G. (2023) 'Non-compete Agreements in a Rigid Labour Market: The Case of Italy', IZA Discussion Papers 15641, Institute of Labor Economics (IZA), Bonn.
Cali, M., and Presidente, G. (2023) 'Product Market Monopolies and Labor Market Monopsonies', Policy Research Working Paper Series 10388, The World Bank, Washington, CO.
Card, D. (2022) 'Who set your wage?', *American Economic Review*, **112**: 1075–90.
Datta, N. (2023) 'The Measure of Monopsony: The Labour Supply Elasticity to the Firm and its Constituents', CEP Discussion Paper.
Datta, N. (2024) 'Local Monopsony Power', CEP Discussion Paper No. 2012, London.
Deb, S. *et al.* (2022) 'What Drives Wage Stagnation: Monopsony or Monopoly?', *Journal of the European Economic Association*, **20**: 2181–225.
Dodini, S. *et al.* (2023) 'Monopsony, Job Tasks, and Labor Market Concentration', NBER Working Papers, Cambridge, MA.
Fanfani, B. (2022) 'Tastes for Discrimination in Monopsonistic Labour Markets', *Labour Economics*, **75**: 102107.
Guanziroli, T. (2022) 'Does Labor Market Concentration Reduce Wages? Evidence from a Retail Pharmacy Merger'. https://conference.iza.org/conference_files/LaborMarkets_2022/guanziroli_t32516.pdf
Jarosch, G., Nimczik, J. S., and Sorkin, I. (2024) 'Granular Search, Market Structure, and Wages', *Review of Economic Studies*, **91**: rdae004.
Lamadon, T., Mogstad, M., and Setzler, B. (2022) 'Imperfect Competition, Compensating Differentials, and Rent Sharing in the US Labor Market', *American Economic Review*, **112**: 169–212.
Langella, M., and Manning, A. (2021) 'Marshall Lecture 2020: The Measure of Monopsony [Monopsony in the UK]', *Journal of the European Economic Association*, **19**: 2929–57.
Luccioletti, C. (2022) "Labor Market Power Across Cities". CEMFI Working Paper No. 2214, Madrid.
Manning, A. (2003) *Imperfect Competition in Labor Markets*. Princeton: Princeton University Press.
Manning, A. (2011) 'Chapter 11 - Imperfect Competition in the Labor Market', in D. Card and O. Ashenfelter (eds) *Handbook of Labor Economics Vol. 4*, pp. 973–1041. San Diego, CA, USA: Elsevier.
Manning, A. (2021) 'Monopsony in Labor Markets: A Review', *ILR Review*, **74**: 3–26.
Marinescu, I., and Hovenkamp, H. J. (2019) 'Anticompetitive Mergers in Labor Markets', *Ind. LJ*, **94**: 1031.
Marinescu, I., Ouss, I., and Pape, L.-D. (2021) 'Wages, Hires, and Labor Market Concentration', *Journal of Economic Behavior & Organization*, **184**: 506–605.
Martins, P. S., and Melo, A. (2024) 'Making their Own Weather? Estimating Employer Labour-Market Power and its Wage Effects', *Journal of Urban Economics*, **139**: 103614.
Mertens, M. (2021) 'Labour Market Power and Between-firm Wage (in)Equality', IWH Discussion Papers 13/2020. Halle Institute for Economic Research (IWH), Halle.
Paker, M. M., Stephenson, J. Z., and Wallis, P. (2024) 'Nominal wage patterns, monopsony, and labour market power in early modern England', *Economic History Review*, 1–28.
Popp, M. (2023) 'Minimum Wages in Concentrated Labor Markets', Tech. rep. arXiv. org.
Posner, E. A., and Marinescu, I. E. (2020) 'Why Has Antitrust Law Failed Workers?', *Cornell L. Rev.*, **105**: 1343.

Saidi, F., and Streitz, D. (2021) 'Bank Concentration and Product Market Competition', *The Review of Financial Studies*, **34**: 4999–5035.
Schubert, G., Stansbury, A., and Taska, B. (2024) 'Employer Concentration and Outside Options'. Available at SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3599454
Shapiro, C. (2019) 'Protecting Competition in the American Economy: Merger Control, Tech Titans, Labor Markets', *Journal of Economic Perspectives*, **33**: 69–93.
Sokolova, A., and Sorensen, T. (2021) 'Monopsony in Labor Markets: A Meta-Analysis', *ILR Review*, **74**: 27–55.
Sulis, G. (2011) 'What can Monopsony Explain of the Gender Wage Differential in Italy?', *International Journal of Manpower*, **32**: 446–70.
Suresh, N., Eric, P., and Glen, W. (2018) 'Antitrust Remedies for Labor Market Power', *Harvard law review* **132**: 536–601.

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