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MONOPSONY IN LABOR MARKETS: EMPIRICAL EVIDENCE FROM ITALIAN FIRMS

Abstract. I leverage on a matched employer-employee database drawn by INPS archive representative of the universe of Italian private sector workers to investigate how labor market concentration affects wages and employment in Italy. I compute concentration measures relying on new hires finding that LMs aren't on average concentrated, despite showing relevant heterogeneity. I then investigate the endogenous relationship with wages and employment finding negative effects. I finally develop a novel IV strategy based on M&As to explore whether they increase concentration at a market-level and to find a reliable source of variation to identify their effect. First stage estimates indicate that only mergers raise significantly concentration, while other events don't. Relying on the former estimated elasticities range between 0.09 and 0.14 p.p for wages and between 0.68 and 0.77 p.p for hires.

Keywords. Monopsony, Wages, Labor Market Concentration, Mergers, Employers' Power, Hires

1. INTRODUCTION & LITERATURE

The labor economics literature has often defined labor market monopsony a situation where employers' power as a buyer of labor services is not compensated by sufficient workers' bargaining power and workers have low or no outside options.

Strictly speaking, the term monopsony refers to the extreme case in which one buyer dominates a specific upstream market and, to maximize its profits, can fix input purchases and prices below the level that maximizes social welfare (OECD, 2019). There's evidence that monopsony can explain wage inequality and falling labor shares trends from a macro perspective, while from a micro one it can explain trends in wage, productivity and employment dynamics as well as the gender wage gap and migration phenomena (Manning, 2020). For these reasons, there is growing literature trying to explore this topic. My work aims at contributing to this literature by calculating a novel long-period measure of labor markets concentration in Italy, identifying the effect of concentration on wages and employment across time and linking concentration to M&A's dynamics to find a reliable source of variation. Many papers have recently studied the issue of growing concentration in labor and product markets. Most of them have focused on US economy, which is for many reasons different from the European and Italian one. Moreover, the available research in these fields has not focused on the labor market side of this issue, thus making use of microeconomics tools to evaluate monopsony evolution through time, and its impact on the labor market. Guitierrez and Philippon (2020) analyze the growth in superstar firms - in terms of size and productivity - from 1960 up until the present.

They find a steady decline in all the dimensions, thus suggesting that the fear of weaker competition in US labor market is mostly unfounded. An ongoingwork byMertens (2021) relying on German manufacturing firm-level data shows that wage inequality is increasing due to across firms' heterogeneity. Deriving firms' specific measures of MRPL, the author proves that among the right tail of firms' distribution - those bigger, more productive and paying higherwages - there's an increasing labor market power (i.e., the wedge between MRPL and wages). The work proves that growing wage inequality hence is not due to lower-paying and low productive firms, but rather to superstars paying already high salaries but still lower than marginal revenues. A recent paper by De Loecker *et al.* (2020) based on US firm-level data investigates the evolution in market power and its relationship with firm markup and revenues. It finds that from 1980 onward markups have risen from 21% to nearly 61% in 2014, while average profit rates have increased from 1% of sales to 8%. Authors attribute this rise in market power nearly exclusively to the increase for the firms with the highest markups already, the so-called superstars. The distribution of markups has become more skewed, while the median of the distribution remains unchanged. Berger *et al.* (2019) derive instead a theoretical model to predict the evolution of market power estimated through the HH index in the US firms' market. Calibrating their model on US census data, they prove that the payroll weighted wage-bill Herfindahl fell from 0.20 to 0.14 between 1976 and 2014 indicating a significant decrease in labor market concentration. This in turn has increased labor share of income by 3% between 1976 and 2014. Different explanations were found in a recent paper by Summers and Stansbury (2020) where they, using aggregated macro data from the '80s showing the decline in labor share and increase in aggregate markups, profits and revenues driven by a small subset of superstar firms', manage to link these trends to the decline in workers powers measured by the unionization rate. Summing up, the literature indicates that with different methodologies and data labor market concentration has increased steadily, is associated with a decrease in labor share and an increase in markups and productivity. However previous works are mostly based on US data, while the decline in labor share and the rise in labor market concentration is a worldwide phenomenon. More evidence regarding Europe and Italy is needed to prove whether the same patterns have emerged. Moreover, these works do not identify causal relationships between rising concentration and labor market outcomes. Autor *et al.* (2019) analyzing micro panel data from the US economic Census since 1982 document empirical patterns to assess the fall in the labor share due to the rise of superstar firms. Sales concentration is rising across a large set of industries. Those industries where concentration has risen the most exhibit the sharpest falls in the labor share, and the between firms' reallocation of the labor share is greatest in the industries that are concentrating the most. Aggregate markups have been rising and the industries that are becoming more concentrated are also becoming relatively more productive and innovative. Finally, these patterns are observed not only in US data but also in OECD countries. Analyzing the nurses' labor market in California, Matsudaira (2010) finds negligible evidence of growing monopsony, thus hindering the growing concerns in the US about trends in the labor share and rising market power. Azar, Marinescu and Steinbaum (2019) contribute to this growing debate by calculating measures of market concentration in more than 8000 US local labor markets for the most frequent occupations on CareerBuilder.com. They prove that concentration is high and increasing and that is associated with lower wages. Few works have also tested Manning (2003)'s predictions: increasing monopsony reduces workers' bargaining power and increases that of the employers, thus pushing wages downward. However, due to the differences between the US and European labor market in terms of employment protection legislation and wage setting, further discussion when it comes to Europe is needed. A stream of research has focused primarily on the causes of an increase in monopsony in the labor market. An increase in monopsony might hinder both worker and consumer welfare. This information has led US and in turn European authorities to warn governments on the feasible detrimental effects. OECD (2020) provides a list of main determinants of monopsony (see also Sulis, 2011): searching costs, absence of coordination, information asymmetries, regulatory barriers limiting labor mobility, workers inertia, and lack of mutual recognition of licensed professions. OECD (2019) highlights also the growing dangers induced by an unbalanced relationship between employers and employees, claiming that it might be addressed by better regulation and more effective enforcement. The authors state that monopsony tends to emerge in situations where there are few, large firms, and where frictions in the labor market, preventing workers from easily switching jobs in response to changes in wages or working conditions, are considerable[1].

Considering thus the characteristics of the Italian labor market monopsonistic patterns might arise and expand. Langella and Manning (2021) provide the most recent and comprehensive work ad dressing monopsony from a microeconomic and theoretical perspective. They state that the attention should shift from whether monopsonistic power exists to what are its effects and how to measure it. They also discuss the most relevant methods to estimate employers' power, identifying as the most appropriate the elasticity of the labour supply curve facing the firm, whose degree gives the intensity of employers' power in a market. They also point at the fact that this power is more effective on entrants rather than incumbents. Sokolova and Sorensen (2020) meta-analysis sum up more than 1300 firm-level estimate of labor supply elasticity across countries and years obtained with a wide range of different techniques and data finding that on average there is strong evidence of monopsonistic frameworks, even though characterized by high variation. Estimations regarding Europe are higher than those regarding new world countries, suggest ing thus that European labor markets are more competitive. Regarding instead Italy, Sulis (2011) studies wage elasticity in a sample of workers drawn by *INPS* finding that a positive relationship between firm size and wages can be interpreted as a positively sloped labor supply curve, which is a sign of the presence of monopsony (Manning, 2003). Endogeneity is addressed by relying on an exog nous shock (i.e., *Scala Mobile reform*[2]). Sulis finds that in the pre-reform period there was a strong negative relationship between wages and employment that becomes less significant in the post-period (with a stronger effect for men), which indicates the presence of monopsony. The latest reforms in the Italian legislation stringency provide additional motivation for my analysis.[3] The

[1] Remedies are: extend the coverage of labor market regulations, more aggressively enforce rules against employ ers colluding in the labor market (i.e. Nonpoaching agreements), limit the range of Noncompete agreements, use labor market regulation to redress information asymmetries between employers and workers and finally reduce searching frictions and costs and enhancing labor market mobility.

[2] Basically, it was an automatic indexation of workers' wages approved in 1992 aimed at protecting their purchasing power from increases in the cost of living.

[3] Fornero's reform (2012) and Jobs Act (2015).

main works addressing labor market concentration in Europe are Marinescu *et al.* (2021), Azkarate-Askasua and Zecezero (2020), Bassanini *et al.* (2021) and Dodini *et al.* (2020). In the first, the authors use French panel microdata combining information regarding firms and workers' wages, adding the interaction between unionization rate and the local HH indexes. They find that the standard neg ative effect of concentration on wages becomes positive. In the second, relying on longitudinal employer-employee data, the authors estimate the evolution of concentration in French LLM's estimating the impact of firms' shares within each market on wages. They both rule out the potential endogeneity problem between wages and concentration by relying on two different instruments. On average, local labor markets concentration has increased and the higher the firm share, the lower is the yearly average wage paid to workers, confirming Manning (2003)'s prediction. Bassanini *et al.* (2022) instead investigate the effect of con centration across LLM's in France on incumbents' wages, rather than entrants, finding a negative and significant elasticity of approximately (0.015-0.025) p.p.. Considering the high stringency of French labor market legislation and wage rigidities, the authors believe that their estimates reflect the lower bound of labor market concentration effect on wages. Dodini *et al.* (2020) rely on concentration to proxy employer's power with a slight but significant change in the methodology. They compute thick concentration measures of workers flows in Norway across clusters of skills, as classified by the O'NET source, rather than industries and occupations. They find that this measure is more relevant in explaining standard labor outcomes than previous ones because these tend to overestimate concentration not taking into consideration workers' mobility within the same skills clusters and across occupations and industries. Their findings also indicate that women and migrant density within higher concentrated markets might additionally explain the gender wage gap and productivity dynamics. These predictions are expressed also in Manning (2020) and empirically tested in Detilleux and Deschacht (2021). They found relying on US administrative microdata that labor supply elasticity of women is lower than that of men and that children's presence has a hampering and monotonic effect for women only. According to the authors, this result indicates that women self-select into more concentrated markets where employers' power is higher and more exerted also because children's presence reduces outside options.

2. EMPIRICAL STRATEGY

I aim to contribute to this growing literature calculating the intensity through time of employment concentration within and across Italian labor markets. A market is defined as an interaction of a region, an industry and an occupation, and it's followed for each year. The goal is to provide evidence on the evolution of employers' power estimated relying on the Herfindahl-Hirschman index within and across Italian labor markets (Azar, Marinescu and Steinbaum, 2019; Marinescu *et al.*, 2021). I rely on a flow-based measure of concentration, rather than the standard one based on stocks. In fact, to the extent that new hires adequately measure available job opportunities for workers, it paints a more precise and dynamic picture of how markets' concentration evolves through time. Marinescu *et al.* (2021) prove empirically why flow-based measures are more adequate: they calculate the HHI on both stocks and flows of employment proving that they correspond to different concentration levels. For example, in their data, the standard value of 0.25 for highly concentrated markets based on stocks corresponds to 0.7 in the flow-based measure. Hence, relying on the stock-based measure seriously tends to underestimate the actual levels of concentration across labor markets. A concentration measure based on new hires is also relevant for the wages of incumbents because it reflects their potential outside options across points in time (Bassanini *et al.*, 2022), still assuming that hirings measure correctly available opportunities in the job market. I then move to estimate the impact of labor markets concentration on workers' wages and employment relying on multiple FE's specifications, addressing in turn endogeneity through an IV strategy based on mergers happening across labor markets and years.

2.1 Data

To calculate concentration and measure wages and hires, I exploit *LoSaI* (Appendix 6.1) which provides several dataset containing information on all working spells including remunerations of a sample of workers and of linked firms – such as size class (discrete as classified in 14 brackets from 15 to over 500 employees) and industry (2-digits ATECO cells) from 1985 to 2018 that can be associated to registry information of the same workers, including the region of residence. I select only new hires in the period 2005-2018, as theoretical and empirical predictions indicate that employers' power compresses entrants' wages rather than long-period incumbents which are protected by open-ended contracts. I define new hires as the spells activated for each individual in a given year in which firm does not match the one for which the same individual has worked the previous year (Bassanini *et al.*, 2022). I additionally exclude transformations keeping only newly activated spells. Finally, I delete for each worker repeated observations within the same year keeping the longest spell. I compute the main dependent variable daily wages by dividing the overall gross remuneration for each employment contract by the number of worked days recorded both by *LoSaI*, thus ruling out the likelihood of measurement errors. The number of records with value of 0 in the dependent variable is less than 50,000 and they are discarded in the regressions.

TABLE 1 • SUMMARY STATISTICS FOR AGE AND DAILY WAGES, NOMINAL AND REAL. REAL WAGES ARE OBTAINED DEFLATING NOMINAL DAILY WAGES WITH THE 2015 CPI (SOURCE: ISTAT).

variable	N	mean	sd	min	p1	p50	p99	max
Age	3,573,677	35.556	11.194	18	18	34	62	67
Daily wage	3,573,677	61.079	42.146	0.000	0.000	56.494	213.462	700.000
Daily wage (real)	3,573,677	64.393	44.380	0.000	0.000	60.122	226.453	704.935

Note: Observations are 3,573,677 entrants' employment contracts defined as those newly activated for each individual who was not working in the same firm the previous year.

2.2 Measuring concentration within labor markets

A labor market is defined as an interaction between an industry *s*, and occupation o and a region *r* (Appendix 6.1). Industries are 2-digits cells classified according to the ATECO brackets, occupations are *employees*, *managers*, *middle managers apprentices* and *workers*, while regions are those of residence of workers. I can therefore estimate concentration across Italian labor markets relying on the Herfindhal-Hirschman formula:

$$\mathrm{HHI}_{m,t} = \sum_{\#d_m} s_{d,t}^2 \qquad (1)$$

where $\#d_m$ represents the number of class sizes in each market m and s is the ratio of the number of new hires for the representative firm in class d in m in t over 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 underlying idea beyond 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 it. The fact that larger firms or plants pay higher wages, and viceversa, in the US as well as in Europe is well established in the literature (Krueger and Summers, 1988; Brown and Medoff, 1989; Oi and Idson, 1999). In Italy, Bertola and Garibaldi (2001) find that both the mean and the variation of wages depend on firms' size while Mion and Naticchioni (2009) find that firms' size explains a relevant portion of spatial and time variation in wages.

2.3 Evidence on markets and concentration

I compute concentration measures for approximately 6,000 markets. However, several markets have only one spell which induces an upward bias in the estimation of the HHI as with one spell only the index for a mechanical bias induced by the formula in Equation (2) is equal to 1, the value that indicates the highest level of concentration. This is a widely documented weakness of the HH index. To address it, I follow a common procedure in the literature and I delete all those market-year tuples with one spell only. Finally, I obtained an almost balanced panel of 47,727 market-year tuples regarding 5,008 markets in Italy between 2005 and 2018 containing 3,600,00 employment contracts associated with 1,400,000 workers.

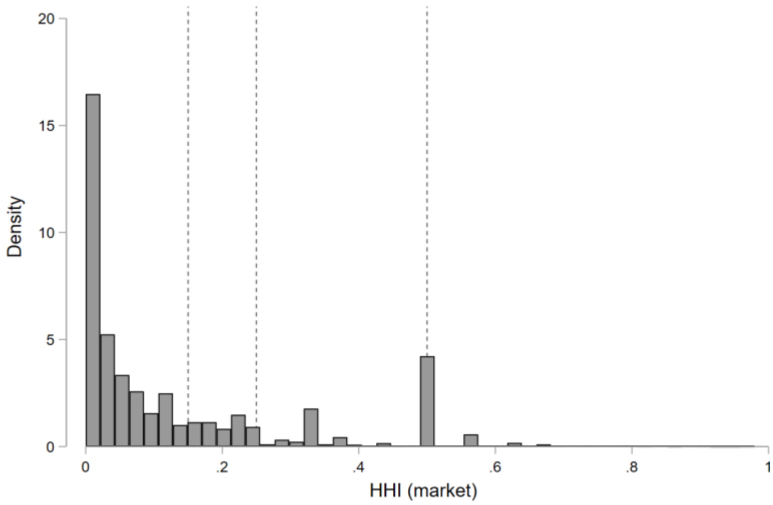
TABLE 2 • SUMMARY STATISTICS OF CONCENTRATION MEASURES ACROSS MARKETS (*M*), INDUSTRIES (*I*), REGIONS (*R*) AND OCCUPATIONS (*O*) ONLY RESPECTIVELY.

variable	N	mean	sd	min	p1	p50	p99	max
HHI_m	47,727	0.136	0.174	0.000	0.000	0.054	0.625	0.979
HHI_i	1,064	0.155	0.087	0.006	0.027	0.141	0.424	0.642
HHI_r	280	0.148	0.040	0.088	0.094	0.138	0.269	0.291
HHI_o	84	0.211	0.094	0.091	0.091	0.206	0.363	0.363

Source: Own calculation based on LoSaI, 2005-18.

Note: indexes are calculated according to formula (2) relying on entrants' spells those newly activated for each individual who was not working in the same firm the previous year. For occupations, industries and regions indexes are calculated as averages of markets HHI's within each of them.

FIGURE 1 • HISTOGRAM OF CONCENTRATION ACROSS 5,008 LOCAL LABOR MARKETS IN ITALY FROM 2005 TO 2018

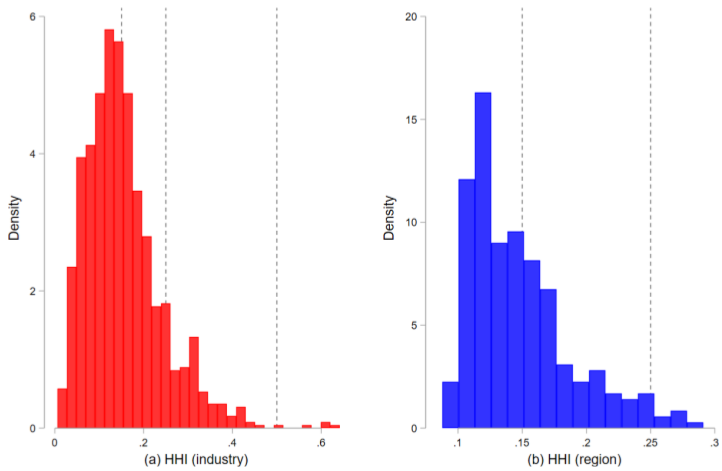


The dotted lines represent the standard thresholds to define respectively low, medium, high-medium and high levels of concentration. Markets are defined as combination of regions, industries and occupations. Markets HHI's are calculated as the squared sum of class size shares, where the share is calculated as the ration between hires by market-year tuples of the representative firm in each size class and the total number of hires in that market. Observations are 47,727 market-year tuples.

On average, concentration across markets in Italy is moderate: the median value is by far lower than the standard threshold indicating a medium level of concentration and only a few markets can be classified as concentrated. However, the average value of concentration is approximately 0.14, indicating instead a medium concentration. This proves that the distribution is right-skewed: most of the markets are not concentrated while only a few are.

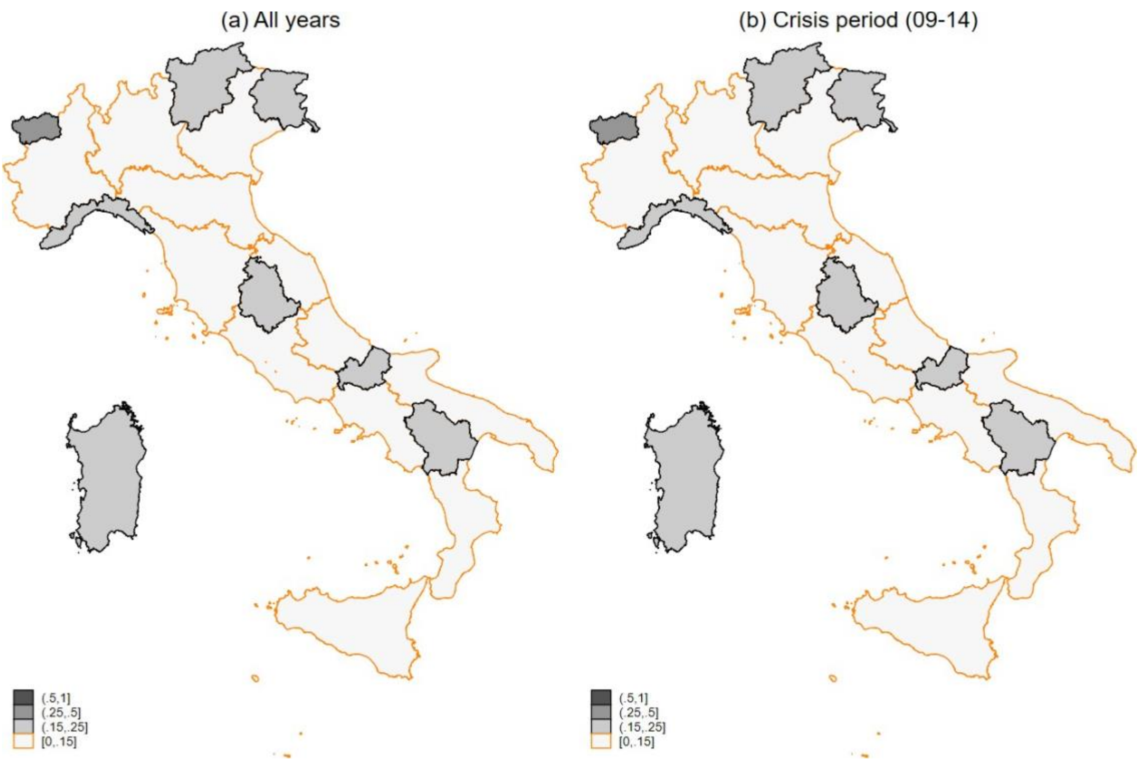
Summing up, concentration distribution in Italy is heterogeneous: most of the markets show low value while few are highly concentrated driving the average value upward. When computing the measure across regions, industries and occupations only concentration increases: on average, values indicate approximately medium concentrated markets, with occupations having a value that is slightly lower than the high concentration threshold. One concern is that concentration varies with time peaking during the recessions thus eventually exacerbating their detrimental effect on workers' welfare. However, my results point in a different direction: concentration is heterogeneous across time and during the peak of the financial crisis (2009-2014 in Italy) it does not differ significantly from the whole period as proved by Figure 3 and Figure 5. Therefore, it does not seem that labor con centration is an additional channel through which recession might damage employment and wages.

FIGURE 2 • HISTOGRAMS OF CONCENTRATION ACROSS INDUSTRIES AND REGIONS IN ITALY FROM 2005 TO 2018.



Industries are 76 2-digits ATECO cells while regions are the 20 Italians. The dotted lines represent the standard thresholds to define respectively low, medium, high-medium and high levels of concentration. HHI's for industries and regions are calculated as averages of markets HHI's' within a given industry cell or a given regions. Markets HHI's are calculated as the squared sum of class size shares, where the share is calculated as the ration between hires by market-year tuples of the representative firm in each size class and the total number of hires in that market. Observations are respectively 1,064 industry-year and 280 region-year tuples.

FIGURE 3 • CONCENTRATION MAPS OF ITALIAN REGIONS BETWEEN 2005 AND 2018 IN PANEL (A) AND ONLY DURING THE CRISIS IN PANEL (B).



Crisis period goes from 2009 to 2014. Colors indicate the standard boundaries defining low, medium, highly medium and high levels of concentration. HHI's for regions are calculated as averages of markets HHI's' within each region and across all years in Panel (a) and for 2009-2014 in Panel (b). Markets HHI's are calculated as the squared sum of class size shares, where the share is calculated as the ration between hires by market-year tuples of the representative firm in each size class and the total number of hires in that market. Observations are 280 region-year tuples.

3. RESULTS

3.1. Concentration effect on wages

To test the impact of concentration across Italian labor markets on entrants' wages I estimate several fixed effects specifications, relying on the evidence described in Section 2.3. I estimate the following model:

$$log(Y_{i,m,dj,t}) = \delta_i + \mu_m + \gamma_s + \Gamma_{r,t} + +\Lambda_{d,t} + \Phi_{o,t} + \beta_t + \theta log(HHI_{m,t}) + \Gamma Z_{i,t} + v_{i,m,dj} \quad (2)$$

where i indexes workers, r regions, o occupations, j firms, d class sizes, s industries, and t years. Y is the gross daily remuneration for each yearly spell of worker i in region r, with occupation o, in firm j of class size d and industry s in year t. The others are worker-level covariates, such as a quadratic polynomial for age and spells length to proxy individuals' working experience and on-the-job specific working experience. Markets m are defined as interaction of r, o and s in t and shares are calculated within each d. θ should be interpreted as the elasticity of entrants' wages with respect to market concentration, as the model is specified as a loglog. Models are estimated with OLS with multiple FEs (Correia, 2017) assuming that observations are correlated within markets and years (Bassanini *et al.*, 2022). I hence take into the potential effects of shocks involving workers within the same market and in a given year. I do not allow for a wider clusterization at a market level as it's presumably unlikely that shocks affecting market concentration persist across all years. I exploit hence both cross-sectional and within time variation in concentration to address its effect on workers' 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. I hence aim to reduce the presence of time invariant characteristics at a worker and market level. Thanks to the length of the panel, market and worker FE's detect a considerable amount of wages variation. I also control for occupation-year, region-year and size-year fixed effects to take into account potential time-varying confounding effects influencing jointly concentration and wages at different levels. Results in Table 3 indicates that the relationship between concentration and wages exists but overall is weak, as it changes by adding additional covariates. The sign switches when I add market fixed effects, suggesting indeed that time-invariant unobserved heterogeneity at a market-level do explain a considerable amount of variation of both wages and concentration. In the latest specification, the elasticity of wages with respect to concentration is negative, even though slightly significant and weak. The magnitude and significance of the estimates across the specifications indicate that the specifications suffer from endogeneity, mainly due to the simultaneous relationship between wages and concentration. Higher concentrated markets might be also those whose firms have attracted more skilled and productive workers offering higher wages. The opposite holds in markets where firms have less incentive to reward workers' skills and thus end up being less concentrated. I'll extensively discuss endogeneity in Section 3.3.

3.2 Concentration effect on employment

Literature has also predicted theoretically and proved empirically that labor market concentration affects employment. The effect might go through two channels: on the extensive margin, a highly concentrated market prevent firms to enter the competition and reduce employment while on the intensive margin firms holding power have the incentives to reduce labor input to implement a cost saving strategy. I'm not able to disentangle these two mechanisms because I do not observe in my data workers' in and out flows of a representative population of firms. However, I can test whether employment decreases when concentration increases. I measure new hires as the number of new employment contracts activated within each market-year tuple and estimate the Equation:

$$log(F_{m,t}) = \delta_m + \Phi_s + \gamma_{o,t} + \Theta_{r,t} + \beta_t + \theta log(HH_{m,t}) + \phi X_{m,t} + v_{m,t} \quad (3)$$

where m indexes markets, δ and β represent market and year fixed effects and γ, Φ and Θ are occupation-year, industry and region-year fixed effects. X are market-level controls. Following Marinescu *et al.* (2021) I measure employment as a flow: the number of labor contracts signed in a market during a year and denoted by $F_{m,t}$. I estimate Equation (4) with OLS adding fixed effects at a market-level and a full set of time-varying market-level controls. θ should be interpreted as the elasticity of employment with respect to labor market concentration, as the model is specified as a log-log. X includes controls as the average age and the share of men in the market.

TABLE 3 • ESTIMATES OF ELASTICITY OF ENTRANTS' WAGES WITH RESPECT TO MARKETS CONCENTRATION BETWEEN 2015 AND 2018

Dependent variable: ln(Daily wages)				
	(1)	(2)	(3)	(4)
ln(HHI)	.00209**	-.00152**	.00115	-.0014*
	(.00075)	(.00068)	(.0011)	(.00081)
Observations	2,928,818	2,928,818	2,928,474	2,928,474
spell length & age (squared)	√	√	√	√
part time dummies	√	√	√	√
worker FE	√	√	√	√
year FE	√	√	√	√
industry FE	-	√	√	√
region FE	-	√	√	-
occupation FE	-	√	√	-
size FE	-	√	√	-
reg-ind-occ FE	-	-	√	√
occupation-year FE	-	-	-	√
size-year FE	-	-	-	√
region-year FE	-	-	-	√

SE clustered at a market-year level.
Daily wages are the ratio of overall remuneration and the number of worked days
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Obs are 3,573,677 yearly spells between 2005 and 2018. Note: observations are lower than in the full sample and differ across specifications because singletons are iteratively dropped when including worker and markets FE's.

TABLE 4 • ESTIMATIONS OF ELASTICITY OF EMPLOYMENT WITH RESPECT TO CONCENTRATION AT A MARKET-LEVEL

	(1)	(2)	(3)
	ln(Hires)	ln(Hires)	ln(Hires)
ln(HHI)	-.1166***	-.1167***	-.0948***
	(.00445)	(.00446)	(.00332)
Observations	47,180	47,180	47,180
(mean) sex & age	√	√	√
reg-ind-occ FE	√	√	√
year FE	√	√	√
occupation FE	-	√	-
region FE	-	√	-
industry FE	-	√	√
region-year FE	-	-	√
occupation-year FE	-	-	√

SE clustered at market level
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Employment is measured as the number of newly activated working spells within each market and year. Full sample is made of 47,727 market-year tuples. Markets are 5,008.

Table 4 proves that there is a negative and significant correlation between market-level concentration and employment flows: when (and where) concentration increases, hires diminish. Coefficients are very similar in magnitude across all different specifications and they are very precisely estimated, as the standard errors are all very similar and small. Estimates suffer of endogeneity: concentration and hires do influence each other, even though differently with respect to wages. In fact, due to the Herfindhal-Hirschman formula, markets with higher spells tend mechanically to have a lower level of concentration while the opposite holds for markets with fewer spells. This induces a negative relationship between the two variables which biases towards zero the estimations of concentration effect, as this mechanical effect covers the true one. Moreover, there might be still shocks influencing hires and concentration simultaneously, such as a massive lay off specific to a market or an industry, that I cannot take into account without relying on a shock moving concentration only.

3.3 Threats to identification

I estimate the models including a full set of fixed effects and controls at a worker and market-level, both time-varying and not. Year fixed effects capture macro shocks – homogeneous across regions, industries and occupations – happening at a national level and possibly influencingwages and firms' hires dynamics, such as workers' out-of-work benefits which are set at a national level, macroeconomic fluctuations and trend effects. Occupation-year, size-year and region-year fixed effects capture instead specific time-varying dynamics across regions – capturing local specific employment dynamics –, firms' size – capturing yearly specific productivity trends for firms of the same size class – and occupations. However, industry-specific time trends, firms' productivity and market tightness shocks raise concerns about the robustness of Equation (3). I'm already controlling for market, occupation-year and region-year fixed effects but not for industry-year. This means that whether during the period of analysis a yearly-industry specific shock affecting wages happens estimates would be biased. Including firms' fixed effects would solve the former, but as described in the introduction *LoSaI* is not representative at a firm-level. *LoSaI* is instead representative across and within firms' size' classes and indeed I include size-year fixed effects. However, the presence of firm-specific characteristics correlated to wages – such as productivity, human capital, employers' attitude and others factors explaining wages heterogeneity – would bias the estimates. Market tightness is an additional threat: I control for both market and region-year fixed effects as proxies. Ideally, I should build more detailed measure of labor market concentration relying on the commuting zones as in the literature (Marinescu *et al.*, 2021; Bassanini *et al.*, 2022; Autor *et al.*, 2019) to precisely take into account local employment dynamics. However, I have no access to further segmentation beyond the regions in *LoSaI* and hence I cannot improve the specification. Another concern is raised by the absence of product market concentration: its omission presumably biases the estimates downward as it's established in the literature (Marinescu *et al.*, 2021; Dodidi *et al.*, 2020; Bassanini *et al.*, 2021) that it's correlated positively with concentration and negatively with wages. Unfortunately, I don't have access to firm-level information regarding prices and markups and hence I cannot improve the specifications in this sense. However, the bias is likely attenuated thanks to market and year FEs. The latter issue is reverse causality, which is induced by time-varying market-level shocks influencing simultaneously wages and concentration that I do not control for. The main one is again market tightness which is correlated to both wages and concentration at a market-level as it depends simultaneously on hires and vacancies. Nevertheless, there might be other confounding effects. Industry-year shocks influencing simultaneously concentration and wages – such as technological or trade shocks targeting specific industries in specific years – might occur and would bias the estimates as I do not control for industry-year fixed effects. Additionally, a mass layoff occurring in a given market certainly would increase concentration, but at the same time also has a direct and significant effect on wages and hires. Ideally, I should control for market-year fixed effects, ruling out the presence of all kinds of confounding effects at this level. However, collinearity likely arises with respect to other fixed effects thus invalidating the estimates of the true effect in the exam. Moreover, there's an additional ongoing relationship between wages and concentration: on one hand, everything else equal, higher wages attract more workers and therefore increase markets' concentration. On the other hand, if there is labor market power on the employer side, I expect two workers with the same characteristics to be paid differently depending on the specific local labor market concentration. These twomechanisms cancel out and their interaction does play a relevant role in terms of the magnitude of the bias, as the endogenous estimates contained in the empirical literature are bounded to zero with respect to those exogenous. The employment specification in Equation (4) additionally suffers from reverse causality because of the mechanical relationship that assigns higher concentration to markets with fewer spells. The opposite instead holds for markets with more spells. Again, I expect the exogenous estimates to be greater in absolute terms because not constrained towards zero. To rule out all these biases I have to rely on a shock triggering a variation in concentration orthogonal with respect to wages and employment dynamics.

3.4 Addressing endogeneity through mergers

The issues previously described can be solved by relying on a shock moving only concentration. This variation should rule out the joint effect of any labor demand and offer shocks at a market-level influencing contemporaneously concentration and the outcomes of interest. Furthermore, it should also be orthogonal with respect to the joint presence within and across markets of that mechanism inducing a positive correlation between concentration andwages. To obtain this exogenous variation I rely on an instrumental variable approach based on mergers and acquisitions. A wide literature has focused on M&A's but mostly in different fields of economics with respect to labor. However, growing theoretical evidence and concerns among competitions authorities and policy makers in US and Europe suggest that mergers and acquisitions might have consequences in the labor market also. Marinescu and Hovenkamp, 2019) discuss the role played by M&A's in the Labor market highlighting the dangers that growing concentration caused by mergers can cause for workers' wages and employment, and thus for the overall welfare. They indeed exhort authorities to consider labor markets spillovers when they evaluate mergers besides those on prices and markups. OECD (2019 and 2020) indicate that merging and acquisitions are a channel through which concentration enhances, and hence should be carefully evaluated by competition authorities. Manning (2020) and (2021) provide a list of environments in which monopsony plays a role and urge competition authorities to address the role played by M&A's. Dodini *et al.* (2021) address the threats posed by mergers to the Norwegian labor market proving that on average concentration is lower than expected and therefore many relevant M&A operations have been denied to safeguard market competition when there was no need to. Marinescu *et al.* (2021) provide one of the few empirical evidence on this topic: they simulate a merger between two top employers in a given industry finding that it would increase concentration significantly with a sizeable detrimental effect on wages and hires. Arnold (2019) addresses directly the issue relying on US data estimating a diff-in-diff comparing outcomes for entrants' workers in markets experiencing mergers with respect to those who don't. He finds that not all mergers events increase concentration and that the effect is not constant along with concentration distribution: it's indeed stronger in higher concentrated markets and negligible for others. Elasticities are significantly higher than those on average estimated in the literature as they range between -0.2 and -0.3 points. This result suggests that, beyond ruling out endogeneity, mergers account for a different channel of concentration variation that results in a more detrimental effect on wages. There's therefore evidence that mergers generate spillovers in the labor market, even though more research is needed to empirically link them to concentration increases and in turn identify effects on the outcomes of interest.

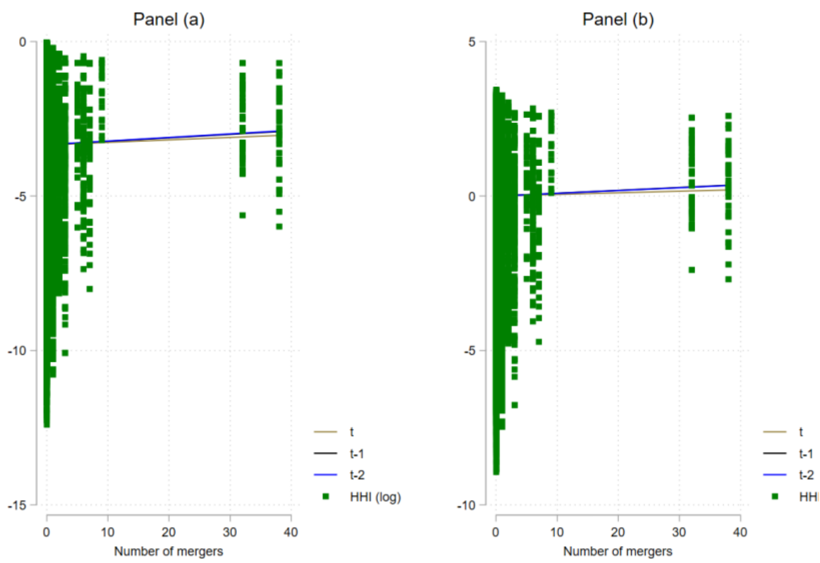
3.4.1 Data

I exploit the *Zephyr* database provided by the Bureau Van Dijk. *Zephyr* is a database whose records are a times series of worldwide rumoured, announced or completed mergers and acquisitions operations of all types (partial or full acquisitions, mergers etc..) from 1997 to nowadays. I select all completed mergers and acquisitions operations whose target country is Italy from 2005 to 2018. For a subsample of these events only I also have information on the number of workers involved as well as the vendor and acquiror size. The final sample contains 5,932 events, associated to 4,237 different acquiror firms and approximately the same number of vendors. On average, approximately 423 events happen per year. For further details on the data see Appendix 6.2. In France and Germany, for example, approximately the same number of domestic operations happened between 2014 and 2018 (Source: *Oxford economics*). Hence, Italian labor market exposure to this phenomenon is relatively weak with respect to other countries. The events recorded are mergers and full or partial acquisitions between firms with different shares: considering instead only the former the number of events decrease to approximately 200.

3.4.2 Identification strategy

The idea underlying the identification strategy is that markets become more concentrated experiencing mergers through time. Markets are defined along three dimensions – occupation, industries and regions – and hence concentration could vary depending on separate channel shocks coming through different levels. The channel I aim to exploit is the national-industry-level variation in concentration induced by mergers. More specifically, I rely on the fact that the more a given industry experience mergers in a given year, the more it will become concentrated. This, to some extent that has to be tested, translates into an increase in labor market concentration for those markets associated with the industries experiencing mergers. The strategy thus is that these events represent a shock at an industry-level able to predict an upward movement in market concentration that involves a further segmentation by occupations and regions. The literature on the relationship between concentration and M&A's (Marinescu *et al.*, 2021; Marinescu and Hovenkamp, 2019; Arnold, 2019) focuses on mergers events only. Arnold (2019) proves that not all M&A's increase concentration, and that only those that significantly do that affect wages. First stages estimates prove the validity of this mechanism in my data: when building the instruments based on all M&A's events selected from *Zephyr* results indicate that they increase concentration only in some specifications and slightly.[4] The opposite holds indeed when considering only mergers events: first stage estimates prove that they always significantly affect concentration. I additionally rely on lagged measures to ensure exogeneity with respect to local labor market dynamics that might be correlated with respect to mergers and wages simultaneously and because merged firms need some time to consolidate and display their power raising in turn concentration.

FIGURE 4 • SCATTERPLOT OF MARKET CONCENTRATION (IN LOG) WITH RESPECT TO THE NUMBER OF MERGERS HAPPENING WITHIN THE SAME MARKET AND YEAR ACROSS 5,008 LABOR MARKETS IN ITALY BETWEEN 2005 AND 2018.



Note: Panel (a) contains market HHI's as calculated in Eq. (2) while Panel (b) contains the seasonally adjusted market HHI's obtained subtracting the yearly means to the HHI's to rule out time trends. Lines represent the predicted values obtained through a regression of log of concentration w.r.t current, one-year and two-years lagged mergers. Mergers event are approximately 200 events in the period of analysis. t-1 and t-2 indicate respectively the number of mergers events happened in the previous and in the previous two years for each market-year tuple considered. Observations are 47,727 market-year tuples.

[4] Results not attached but available.

The positive relationship between market concentration and mergers is proved in Panel (a) of Figure 4. The relationship persists considering seasonally adjusted market HHI's in Panel (b). Based on this evidence, I build two different instruments defined respectively as follows:

$$IV1 : \forall \text{ t in } [2005{,}2018], \mathrm{I}_t(\#Mergers_{s,t-1} > 0) = 1 \rightarrow \mathrm{HHI}_{m,t} \quad (4)$$

$$IV2 : \forall \text{ t in } [2005{,}2018], \mathrm{I}_t(\#Mergers_{s,t-2} > 0) = 1 \rightarrow \mathrm{HHI}_{m,t} \quad (5)$$

where t-1 and t-2 stand for one and two previous years. More formally, I instrument concentration within each market-year with a dummy variable indicating whether the industry associated with that market has experienced at least a merger event one or two years previous to the current one. On average the number of employment contracts located in markets experiencing full mergers events ranges from 7 to 10% approximately 200250,000 spells depending on whether I rely on 1 or 2 years lagged mergers. Estimates should be hence interpreted as LATE's: differences in the outcomes of interest between treated and not units classified accordingly by the binary treatment which consists in experiencing at least a merger in 1 or 2 years before the current one. Errors are clustered at a market-year (market) level to address the correlation between workers (markets) affected by the same shock. First stage results are displayed in Table 7 of Section 6.3 and prove that the instruments are always significant F-statistics are all by far greater than 10 (Stock and Yogo, 2005) and predict an upward variation in concentration for treated with respect to not treated observations of 14-17 and of 17-21 p.p. with respectively instruments of Equations (5) and (6) and of 28-35 p.p. with both.

3.5 IV estimates

3.5.1 Wages

In this section, I present the IV estimations on wages. I present results for three different specifications: in Panel (a) I rely on the instrument defined in Equation (6), in (b) I rely on the instrument defined in Equation (5) while in (c) I use both.

Results are displayed in Table 5 and prove that concentration has a size able negative impact on entrants' wages. Estimates magnitude and significance differ little across specifications while the IV of Equation (6) seems to be the most relevant. However, all three empirical strategies produce similar results in terms of magnitude. A 10% increase in market concentration induced by the instruments reduces new hires' wages by approximately 0.9-1.4%. Estimates differ from those of the literature: Marinescu *et al.* (2021) preferred elasticities range between 0.067 and 0.052 points, which indicate a reduction in wages following a 10% increase in market HHI of 0.67 and 0.52%. Other works contain similar for entrants and slightly lower for incumbents' elasticities in terms of magnitude. However, my results are more in line with Marinescu *et al.* (2021) simulation as they find a reduction in the new firm wage-bill of approximately 7% following a 10% increase in concentration induced by a merger between two top-employing firms. Arnold (2019) is the only work to address entirely this issue relying on mergers, even though setting up a diff in diff. He estimates elasticities ranging between 0.3 and 0.2 p.p. depending on the controls, which are significantly higher than those on average estimated in the literature. The difference might be due to the use of different identification strategies and exogenous shocks in con centration. Summing up my estimates lay in the middle between those obtained by Marinescu *et al.* (2021), Azkarate-Askasua and Zerecero (2020), Dodini *et al.* (2021) or Bassanini *et al.* (2022) and those obtained relying on mergers as a shock in concentration (Arnold, 2019).

TABLE 5 • IV ESTIMATES OF THE ELASTICITY OF ENTRANTS' WAGES WITH RESPECT TO MARKET CONCENTRATION BETWEEN 2015 AND 2018

Dependent variable: ln(Daily wages)				
Panel (a)	(1)	(2)	(3)	(4)
ln(HHI)	-.319**	-.114**	-.1258**	-.134***
	(.1354)	(.0471)	(.04514)	(.03803)
Panel (b)	(1)	(2)	(3)	(4)
ln(HHI)	-.282**	-.0525	-.0684*	-.209
	(.1189)	(.04419)	(.0404)	(.1754)
Panel (c)	(1)	(2)	(3)	(4)
ln(HHI)	-.300**	-.0920**	-.1052**	-.1393***
	(.0890)	(.0326)	(.0315)	(.0375)
Observations	2,928,818	2,928,818	2,928,474	2,928,474
spell length & age (squared)	√	√	√	√
part time dummies	√	√	√	√
worker FE	√	√	√	√
year FE	√	√	√	√
industry FE	-	√	√	√
region FE	-	√	√	-
occupation FE	-	√	√	-
size FE	-	√	√	-
reg-ind-occ FE	-	-	√	√
occupation-year FE	-	-	-	√
size-year FE	-	-	-	√
region-year FE	-	-	-	√

SE clustered at a market-year level.
Daily wages are the ratio of overall remuneration and the number of worked days
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Obs are 3,573,677 yearly spells between 2005 and 2018. Panel indicate different instruments use: (a) 2-years lagged mergers as in Eq. (6); (b) 1-year lagged mergers as in Eq. (5) and (c) both jointly. Note: observations are lower than in the full sample and differ across specifications because singletons are iteratively dropped when including worker and markets FE's.

3.5.2 Employment

I then move to estimate the effect of a mergers-induced increase in concentration on employment as identified by the three different empirical strategies. Errors are clustered at a market-level to allow observations within the same market to be correlated across time. Results displayed in Table 6 indicate very stable estimates across Panels, with elasticities ranging between 0.68 and 0.77 points. Magnitude is slightly greater than in the literature: Marinescu *et al.* (2021) elasticities range between 0.31 and 0.585 points. The difference might be due to the different framework and identification strategy, as well to a different definition of new hires. They define new hires as those who have employment contract start dates during the quarter of observation deleting those observations whose job spells start on January 1st for each year. I have additionally deleted all transformations keeping only new activations and all observations for each year whose individual was working in the same firm the previous year. Thus, my definition is more conservative, and the higher magnitude might be due to that. Results indicate that following a 10% increase in market concentration hires reduce by slightly less than 7-8 p.p.

TABLE 6 • IV ESTIMATES OF THE ELASTICITY OF EMPLOYMENT WITH RESPECT TO CONCENTRATION AT A MARKET LEVEL BETWEEN 2005 AND 2018

	(1)	(2)	(3)
	ln(Hires)	ln(Hires)	ln(Hires)
Panel (a)	(1)	(2)	(3)
ln(HHI)	-.681**	-.681**	-.692**
	(.2819)	(.2821)	(.2867)
Panel (b)	(1)	(2)	(3)
ln(HHI)	-.771*	-.771*	-.747*
	(.4689)	(.4694)	(.4402)
Panel (c)	(1)	(2)	(3)
ln(HHI)	-.699**	-.699**	-.704**
	(.2791)	(.2794)	(.2792)
Observations	47,180	47,180	47,180
(mean) sex & age	√	√	√
reg-ind-occ FE	√	√	√
year FE	√	√	√
occupation FE	-	√	-
region FE	-	√	-
industry FE	-	√	√
region-year FE	-	-	√
occupation-year FE	-	-	√

SE clustered at market-level
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Employment is measured as the number of newly activated working spells within each market and year. Full sample is made of 47,727 market-year tuples. Markets are 5,008. Panel indicate different instruments use: (a) 2years lagged mergers as in Eq. (6); (b) 1year lagged mergers as in Eq (5) and (c) both jointly.

4. Conclusions

In this paper I investigate empirically the presence of monopsony across Italian labor markets, relying on labor market concentration as the trigger, to identify its effect on entrants' wages and markets' hires. I first calculate a novel measure of concentration based on hires relying on *LoSaI* in the period 200518 that takes into account data structure and representativeness. Concerning the standard index based on employment stocks, one based on flows captures more precisely current monopsonistic dynamics and so improves the identification of the mechanisms in exam. On average, concentration across Italian labor markets is weaker than expected: approximately the median is 0.05 while the mean is 0.135. This indicates that most of the markets are weakly concentrated while only a few are instead highly concentrated. However, as their weight is sizeable, they drive average concentration upward. Additionally, concentration does not vary within time. This indicates that the fear that the financial crisis has damaged workers' welfare through an additional channel does not seem to be supported by empirical evidence. Concentration slightly increases when computed across regions and industries only. The relationship with wages is not straightforward: the estimates across all specifications show different signs and significance. The preferred one points at a negative, but overall weak and slightly significant, effect. This is due to the presence of endogeneity going through several channels. With respect to employment instead, the effect is precisely estimated and negative, even though lowered towards zero due to the presence of endogeneity. I thus try to clean the estimates relying on a novel IV strategy supported by the theoretical predictions that mergers increase concentration. This relationship is confirmed by descriptive and preliminary evidence in my data. I consider only lagged measures to address endogeneity issues and I exploit only mergers events happening across markets and time in the period of analysis to predict a reliable variation in concentration. The instruments, both separately and jointly, explain a sizeable amount of variation in market concentration within time which in turn has a significant and sizeable effect on wages and employment.

Estimated elasticities range from 0.09 to 0.14 points for daily entrants' wages and between 0.68 and 0.77 points for employment. These effects translate into a loss following a 10% increase in market concentration of approximately 0.9-1.4 p.p. for wages and 7-8 p.p. for hires. I try to answer policy concerns arising from different fields of literature indicating that mergers have side effects in the labor market, increasing concentration and damaging in turn workers and overall welfare. However, Italy overall does not experience many mergers, both across markets and within time, and therefore the economic damages identified are not widespread across markets but rather concentrated across a few. Nevertheless, my results corroborate findings and concerns raised in the literature (Marinescu and Hovenkamp, 2019; Arnold, 2019; Marinescu *et al.*, 2021) suggesting that, besides the well-known product market spillovers, also labor market ones should be taken into account by competition authorities when they deal with mergers evaluation.

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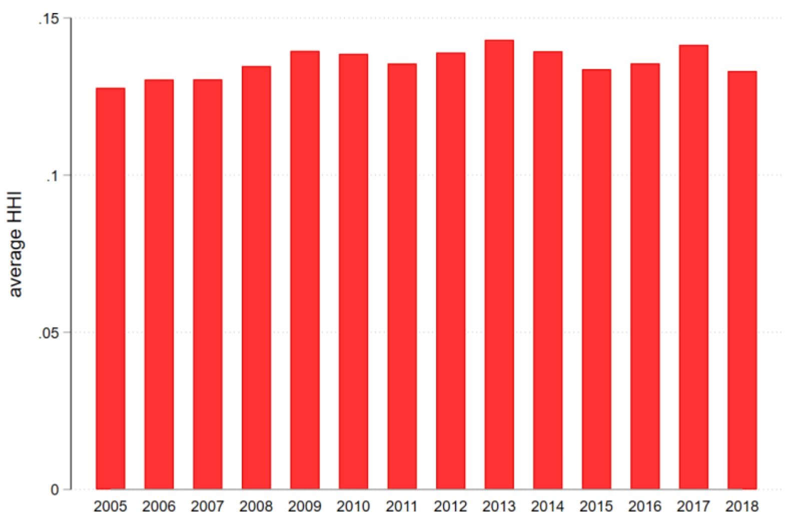
6. Appendix

6.1 LoSai

LoSaI contains several datasets extracted from the *INPS* administrative archive. The first provides a random set of individuals working spells with many information such as gross remuneration, date (d/m/y) of start/end of the spell, type of contract, linked firm to the spell and other standard information from 1990 to 2018. Spells contained are those associated to a random sample of individuals born in days 1 and 9 of any month and year from 1990 to 2018. The second dataset provides instead registry information regarding the same workers - including the region of residence which can be linked to the first through a unique code. In the last dataset, I obtain firms' information regarding class size and industry (ATECO 2007, 2-digits) ranging from 1990 to 2018. Firms can be linked to those in the first dataset with an additional unique code. By merging all these sources, I can get an employer-employee dataset in which I observe working spells remunerations within and across triples as defined by the interaction of firms size classes, regions and industry sectors. However, the sample of firms is not obtained based on stratified randomization by size class, region and industry, but according to workers' date of birth. Firms' population thus is likely not representative of the Italian one.

FIGURE 5 • MEANS OF MARKETS CONCENTRATION ACROSS YEARS FROM 2005 TO 2018



Markets HHI's are calculated as the squared sum of class size shares, where the share is calculated as the ration between hires by market-year tuples of the representative firm in each size class and the total number of hires in that market. Observations are respectively 47,727 market-year tuples.

6.2 Zephyr

The Bureau Van Djik is the worldwide leader providing all sorts of information regarding business and industries, across the world. It also has information on an unrivalled number of deals, stored in the *Zephyr* database. *Zephyr* covers over ten years of history for deals around the world and an even longer history for deals with a European counterpart. It also has information on rumours, as well as announced and completed deals, from the end of the '90 to Nowadays. It covers all types of deals, from standard M&A's to joint ventures, delocalization or closures. The full database contains more than a billion records. Headline, type, status, value and details of the target, acquirer and vendor including country and activities plus regulatory bodies are contained in the database, as well as information regarding target, acquiror and vendor employment volume.

6.3 IV first stages

In this section, I display the results of the first stage estimates for different instruments and different sets of controls. Controls are those in Equation (4) of Table 4. I only present the results with the market specifications controls and not with worker FE's only as in Table 3. Coefficient always positive and significant across all specifications. Results indicate that instruments predict an increase in concentration that ranges between approximately 14 and 17 for the instrument in Equation (5) and between 17 and 21% for that in Equation (6). First stage F statistics are all significantly greater than 10 (Stock and Yogo, 2005). The interesting fact is that instruments even though correlated capture different sources of variation of concentration, as Panel (c) shows that when they are considered jointly they both remain significant and sizeable. Results in Panel (c) indicate that workers belonging to treated markets on average experience higher concentration induced by the instruments by 28-35% with respect to workers in not treated markets.

TABLE 7 • IV FIST STAGE ESTIMATES INDICATING INSTRUMENTS RELATIONSHIP WITH RESPECT TO CONCENTRATION ACROSS DIFFERENT SPECIFICATIONS

	(1)	(2)	(3)
	ln(HHI)	ln(HHI)	ln(HHI)
Panel (a)	(1)	(2)	(3)
IV2	.2109**	.2109**	.1708**
	(.07448)	(.07448)	(.05573)
Panel (b)	(1)	(2)	(3)
IV1	.1740**	.1740**	.1387***
	(.0520)	(.0520)	(.0372)
Panel (c)	(1)	(2)	(3)
IV2	.1973**	.1973**	.160**
	(.0703)	(.0703)	(.0530)
IV1	.1542**	.1542**	.1229***
	(.0456)	(.04567)	(.0336)
Observations	3,573,677	3,573,677	3,573,677
(mean) sex & age	√	√	√
reg-ind-occ FE	√	√	√
year FE	√	√	√
occupation FE	-	√	-
region FE	-	√	-
industry FE	-	√	√
region-year FE	-	-	√
occupation-year FE	-	-	√

SE clustered at market-level
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Panel contain different instruments use: (a) 2-years lagged mergers as in Equation (6); (b) 1-year lagged mergers as in Equation (5) and (c) both jointly. Observations are 3,573,677 employment contracts between 2005 and 2018. Controls are those of Equation (4) and are displayed in Table 4. Errors are clustered at a market level.