Lights and Shadows of Employer Concentration: On-the-Job Training and Wages

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This paper studies the effect of employer concentration on the provision of on-the-job training and wages. I rely on administrative micro-data from Italy and an IV empirical strategy to address the endogeneity of employer concentration. Employers in highly concentrated labor markets provide more training at extensive and intensive margins. Specifically, moving from the 25th to 75th percentile of employer concentration increases the employer's expenditure in training per worker by 50% and the probability that an employer provides any training by 10%. I also find a negative and statistically significant effect of concentration on wages with an elasticity of -0.1. I interpret the results through the lens of an oligopsonistic model. Employers internalize their labor demand on the wages leading them to spend more on on-the-job training per worker. These findings suggest that using employer concentration as a direct measure of labor market competition could underestimate the negative effect of concentration on wages.

Keywords: On-the-job training, Local labor markets, Oligopsony, Human capital

JEL Codes: J24, J23, J21, J42, R12

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1 Introduction

How does employer concentration affect labor markets? There is growing concern about the fact that local labor markets are highly concentrated; that is, the workers within a local labor market are employed by a small number of firms. As a result, policymakers and antitrust authorities have suggested that minimum wages or antitrust policies should be implemented to address this issue. However, to tailor an optimal policy, we need to comprehensively understand how employer concentration affects the labor market, as it affects multiple economic dimensions. Specifically, employer concentration does also influence employer-provided training. Although the traditional literature on human capital has generally focused on formal education, it is clear that human capital accumulation does not end with schools. Moreover, in light of the aging population and the rapid advances in the technological process, training has become even more crucial at any stage of life. Indeed, according to the EU Council (2019), promoting lifelong training is a key challenge for policymakers, as more than half of the current working population has obsolete competencies and requires substantial reskilling and upskilling. Therefore, exploring the determinants that stimulate on-the-job training and how labor market concentration could affect them is essential. Moreover, the aftermath of the Covid-19 pandemic has made it even more crucial to shed light on how to promote on-the-job training, as the pandemic has caused the displacement of a profuse number of workers who will need to adjust and find a job in less familiar occupations (World Economic Forum, 2020; OECD, 2021). Yet, despite its evident relevance, little is known about the mechanisms that drive employer-provided training and whether employer concentration plays any part. A key reason for this is the lack of high-quality administrative data and an identification strategy to deal with the endogeneity of employer concentration.

This paper estimates the effects of employer concentration on wages and employer-provided training through an instrumental variable strategy and sheds light on the mechanisms behind these effects. To do so, I rely on employer survey panel data from Italy in 2015 and 2018 and measure employer-provided training as the amount of monetary resources invested in the training per worker. This information is matched with rich administrative data on firms, which I use to construct employer concentration measures, mainly the employment Herfindahl-Hirschman Index (HHI) at the combination between an industry, region, and year.

Measuring the impact of employer concentration is challenging. Since employer concentration could be correlated with other local unobservable time-varying characteristics that may also affect wages and employer-provided training. To address this issue, I use an instrumental variable approach which instruments variation of concentration for a specific industry through variation in the inverse number of employers in other geographical areas for the same industry (Marinescu et al. (2021)). This IV strategy enables the construction of shocks to local labor market concentration that are plausibly orthogonal to local unobservable characteristics.

As main findings, I document employer concentration's positive and statistically significant effect on the extensive and intensive margin of employer-provided training. A 10 percent increase in concentration is associated with a 10 percent increase in the probability that an employer provides training and a 3 percent increase in the number of euros invested in training. Then, I find a negative and statistically significant effect on wages. A 10 percent increase in concentration decreases wages by around 1.7 percent. The results are robust to several robustness checks, most notably, different measures of the employer concentration and local labor market, including employer fixed effects and several controls at the market level, aiming to control labor market time trends. The results are also robust to the implementation of a different instrumental variable approach based on the Bartik-style instrument, which instruments the variation in local concentration in a particular industry with the predicted change in concentration based on the national employment variation in its sub-industry at the national level, excluding the local area in question.

The second contribution of the paper is to develop an oligopsonistic model to shed light on the mechanism behind these findings. It still needs to be determined whether employer concentration should increase or decrease training provision. In a standard oligopsonistic model, employers choose labor and training provisions as inputs and take the training price as given. In contrast, they internalize the effect of their labor demand on wages. By deciding how many workers to hire, employers consider that their higher demand for labor would lead to higher market-level demand and, in turn, higher wages. The marginal cost of labor is thus larger than the actual wages. An exogenous change in the level of labor concentration increases the relative size of an employer and, in turn, the effect of her labor demand on the market-level demand. This change increases the marginal cost of labor, generating a substitution effect that leads employers to substitute part of the labor with training, consequently increasing the provision of training per worker. However, the increase in the marginal cost of labor also generates a scale or income effect that depending on the functional form of the production function, could lead to a higher or lower total amount of training provision. Adding to this canonical oligopsonistic model, I develop an extension in which training does affect not only the firm production function but also influences workers' labor supply.[1] On the one hand, if workers value training provisions, training can helps employers to increase their recruiting. On the other hand, training can increase workers' outside options and, in turn, increase the poaching threats, reducing the retention of qualified workers. The empirical literature has confirmed this ambiguous effect of training on recruiting and retention, finding results in both directions.[2] The traditional view on this potential ambiguous effect of training on labor supply has been to separate training into two components, general and specific, following the seminal paper of Becker (1964). General training increases productivity not only at the current firm but also at other firms. In contrast, specific training provides skills that are useful only at the incumbent firm but not elsewhere. As a result, general training increases poaching threats, while specific training increases retention. The firm should bear the cost of specific human capital, while the worker should pay for her general human capital. However, it does not explain the empirical evidence of employers paying for apparently general training (Acemoglu and Pischke, 1999a; Autor, 2001). Indeed, much on-the-job training is neither completely general nor completely specific but a combination of both. Any form of training is likely to affect the productivity in some other firms besides the training firm; at the same time, it is also probable that it increases the productivity more in the firm providing the training than elsewhere. Moreover, the effect of training on productivity in other firms depends not only on the skill provided but also on the market conditions. Strong monopsonists might be completely insulated from competition by different employers, and practically all their training provisions could be considered employer-specific. On the other hand, employers in highly competitive labor markets would face a constant poaching threat, and all training provisions could be regarded as general. Therefore, I propose a framework consistent where training is market specific. In this framework, the economy is segmented into markets; a set of firms populates each market. Each market identifies a particular industry that requires a similar set of skills. Workers can move across firms and markets; however, this comes with a cost, as the worker will have to learn the required skills for the job. Through training, a firm provides skills that are useful not only to the incumbent firm

[1] As recently documented, employees value greatly on-the-job training when deciding to which employer to apply. For example, Monster (2021) found that among workers who recently quit a job, 45% would have remained if they were offered more training, while Gallup (2021) observed that 48% of American workers would switch jobs if the new job provided skill training opportunities.

[2] For example, see Munasinghe and O'Flaherty (2005); Jones et al. (2009); Muehlemann and Wolter (2011); Picchio and Van Ours (2013); Mohrenweiser et al. (2019); Dietz and Zwick (2021).

but also to its competing firm within the same market, yet, these skills are useless for firms in other markets. Therefore, according to the market concentration level, the training will work as more or less specific, and the firm will be more or less prone to invest in training.

The third contribution is to provide a potential justification for concentration's surprisingly small negative effect on wages. This finding suggests that other mechanisms balance what the monopsonistic literature expects to be a clear negative effect. One way to partially explain such a discrepancy in the theoretical and empirical predictions is to see how employer concentration affects training. By increasing the training expenditure per worker, workers in more concentrated markets are more productive; thus, ignoring this aspect could lead to underestimating the effect of employer concentration on wages.[3] Moreover, as concentration increases, any training provision becomes practically more specific due to a reduction in poaching threats. As a result, employers could require lower returns in terms of labor productivity from training. I empirically explore these predictions, observing that controlling for employer-provided training, the negative effect of concentration on wages increases by 2 percent, and the impact of training expenditure on workers' productivity decreases by 1 percent for each 1 percent increase in employer concentration. Unfortunately, the employer survey data does not collect information on the firm balance sheets; therefore, this analysis is carried out at the market level through an intention-to-treat strategy, i.e., it assumes that employers in markets with higher average training expenditure are likelier to spend more in training; however, it can not be observed the employers that are actually providing training. Overall, even if not conclusive, these findings support the empirical predictions; however, the impossibility of linking firm performance to training data makes a precise estimate of these predictions unfeasible, which is left for future research.

Related Literature: This paper build and extends on different strands of the literature. First, I contribute to the flourishing empirical literature that analyzes the effect of employer concentration on wages (Martins, 2018; Abel et al., 2018; Rinz, 2022; Lipsius, 2018; Qiu and Sojourner, 2019; Azar et al., 2022; Benmelech et al., 2020; Azar et al., 2020a,b; Arnold, 2020; Schubert et al., 2020; Marinescu et al., 2021; Bassanini et al., 2021; Popp, 2021), as well as a more theoretical literature connecting employer concentration to wage markdown or labor share (Berger et al., 2022; Jarosch et al., 2019; Azkarate-Askasua and Zerecero, 2020; Hershbein et al., 2022). This paper adds to this existing literature by focusing on an additional effect of employer concentration, namely employer-provided training, suggest-

[3] As training, other potential channels could be affected by employer concentration, for example, R&D, skill demand, recruitment, and hiring procedure. All these other possible channels remain for future research.

ing so that the surprisingly small negative effects of employer concentration could be a lower bound and the actual markdown in principle could be larger. Second, I contribute in multiple dimensions to the broader empirical literature studying what promotes employer-provided training (Harhoff and Kane, 1997; Brunello and Gambarotto, 2007; Muehlemann and Wolter, 2011; Jansen et al., 2015; Rzepka and Tamm, 2016; Mohrenweiser et al., 2019; Starr, 2019; Bratti et al., 2021). In this respect, this paper is one of the few to examine the role of employer concentration and the first to address the endogeneity of employer concentration through an instrumental variable approach. Contrary to most, I focus on the demand side of the labor market, i.e. firms, for which data gathering is more difficult and therefore the empirical evidence scantier. Moreover, the literature so far only consider training participation or duration, I further explore the intensity of the employer-provided training, i.e. how much monetary resources an employer has invested in the training. Third, the paper builds a bridge between the traditional literature on training (Becker, 1964; Acemoglu and Pischke, 1998, 1999a,b; Stevens, 1994; Lazear, 2009) and labor market monopsony (Robinson, 1969; Boal and Ransom, 1997; Manning, 2003, 2011) proposing a framework connecting employer-provided training decision and employer concentration. The paper is also close to the heterogeneous literature on the effects of training on productivity (Card et al., 2010; Konings and Vanormelingen, 2015; Hyman and Ni, 2020; Brunello and Wruuck, 2020; Martins, 2021) and on workers turnover (Munasinghe and O'Flaherty, 2005; Jones et al., 2009; Picchio and Van Ours, 2011; Dietz and Zwick, 2021).

The remainder of the paper is organized as follows. Section 2 illlustrates the conceptual framework. Section 3 describes the data. Section 4 presents the empirical specifications and the identification strategy. Section 5 shows the main results with robustness checks. Finally, Section 6 concludes.

2 Conceptual Framework

Although the main focus of the paper is empirical, to guide the discussion I construct a conceptual framework to outline the mechanism behind the results. Build on the traditional monopsonistic literature (Robinson, 1969; Boal and Ransom, 1997; Manning, 2003), where employer concentration generates an upward-sloping labor supply curve, leading to wage markdowns and employment misallocation. I include imperfect competition among employers for workers, analogous to a nested competition in the trade literature (Atkeson and Burstein, 2008), as in Berger et al. (2022). I further extend this framework to include employer-provided training.

2.1 Setting

I consider an economy characterized by a representative household, consisting in a continuum measure of homogeneous workers each with one unit of labor supply, and a fixed number of employers.[4] Firms are heterogeneous in two dimensions: (i) they have different exogeneous productivity z_{ij} and (ii) they inhabit a continuum of different local labor markets (from now on, I refer to as just "market") indexed by $j \in [0, 1]$, each market has a different and exogeneously determined number of firms (M_j). Workers when decide to which market and employer to supply their labor, they do not consider only wages, but they have individual preference for each market and firm, as standard in the classical monopsonistic literature. This causes firms to be differentiated from the workers perspective, generating an upward labor supply curve and allowing employers to exert some market power, i.e. to set a wage markdown over workers productivity. The rationale of these workers idiosyncratic preferences for employers and markets are generally motivated by human capital specificity.[5] Each worker has a specific set of skills or talents, and at the same time, firm requires a different bundle of competencies. If a worker does not possess all the required competencies requested by a firm to actually perform the job she will have to exert more effort. Consequently, a worker will be more willing to work for a job for which she possesses all the required competencies even for a lower wage.

The advantage of this framework is that it allows to include training naturally. Employer provided training will not only impact the worker productivity, but it will also have an ambiguous effect on the labor supply faced by an employer. Specifically, the framework allows to model the observed ambiguous effect of training in either retaining/attracting new workers or increasing the probability that the trained employees are poached by other firms. Assuming that markets share a similar set of required skills, an employer by offering training reduces the amount of effort a worker has to exert to apprehend these new skills, increasing, as a consequence, the willing of outside workers to move into that market. On the other hand, within a market, as the skills required in a market are similar, by increasing

[4]Through the paper, I use the terms firms and employers interchangeably.

[5]Alternative justifications for the idiosyncratic workers preferences are job search frictions and worker-firm specific amenities (Robinson, 1969; Boal and Ransom, 1997; Manning, 2003).

the number of skills taught to her employees, a employer increases the probability that they move to another competing firm in the same market.

Household's problem

The household finds the goods that the continuum of firms produce to be perfect substitutes, and hence trades in perfectly competitive economy-wide market. The price of this indistinguishable final good is normalize to 1.[6] The representative household chooses the number of workers to supply to each firm (n_{ij}), taking in account the wages offered w_{ij} and the amount of employer training provided t_{ij}.

As standard in the classical monopsony model, the optimization problems are static, i.e. the productivity, number of firms, measure of workers, and markets are constant over time, thus, for clarity I omit the time subscripts.

Formally, the representative household problem reads as follow:

$$\begin{aligned} \max_{(\mathbf{C}, n_{ij})} \quad & u\left(\mathbf{C} - \frac{\widetilde{\mathbf{N}}^{1+\frac{1}{\psi}}}{1+\frac{1}{\psi}}\right) \\ \text{s.t.} \quad & \mathbf{C} = \widetilde{\mathbf{W}}\,\widetilde{\mathbf{N}} \end{aligned}$$

where the aggregate disutilities of labor supply are given by,

$$\begin{aligned} \widetilde{\mathbf{N}} &:= \left[\int_0^1 \widetilde{N}_j^{\frac{\theta+1}{\theta}}\, \mathrm{d}j\right]^{\frac{\theta}{\theta+1}} && , \quad \theta > 0 \\ \widetilde{N}_j &:= \left[\sum_{i=1}^{M_j} \widetilde{n}_{ij}^{\frac{\eta+1}{\eta}}\right]^{\frac{\eta}{\eta+1}} G(T_j)^{-1} && , \quad \eta > 0 \quad \text{and} \quad G(T_j) > 0 \\ \widetilde{n}_{ij} &:= n_{ij} g(t_{ij}) && , \quad g(t_{ij}) > 0 \end{aligned}$$

Where η and θ are the elasticities of substitution between firms and markets respectively. The lower is each elasticity, the greater is the firm market power. Indeed, as η or θ tends

[6]The framework could be extended to include competition also in the product market. However, this extension goes beyond the scope of this paper that focus on firm competition in the labor market in isolation with the effect of product market competition.

to infinity, as firms or markets, respectively, become perfect substitutes, which implies that the workers will supply their labor exclusively to that firm or market which offers the highest wage. On the contrary, as η (or θ) tends to 0, firms (or markets) become perfect complements, and the representative household will supply the same amount of workers in all the different firms (or markets) regardless of the wage offers. From here on, I assume that competing firms within a market are more substitutable than markets, i.e., $\eta > \theta$.[7]

With respect to employer provided training, t_{ij} describes the amount of training provided by the employer i in market j; T_j is the average amount of on-the-job training provided in market j, $T_j = \sum_{i=1}^{M_j} s_{ij} t_{ij}$; and $g()$ and $G()$ describe respectively the labor disutility sensibilities to training at the firm and market level. The rationale is build on the human capital specificity of the workers idiosyncratic preferences. As aforementioned, the rationale behind this assumption is that each market has a specific set of skills required for the job. Thus, by moving from a market to another, workers are requested to apprehend new skills. If the market level of training in that market is high, the amount of effort a worker has to exert to learn these new skills is lower, reducing, as a consequence, the cost of moving into that market. On the other hand, within a market, skills are similar. Therefore, by increasing the number of skills taught to her employees, a firm increases the probability they move to another competing firm in the same market, which is modeled by increasing the disutility for working in that specific firm in that market.[8]

As notation, the tilde denotes indexes, which are not directly observable variables. For example, $\widetilde{n}_{ij}$ describes the labor disutility for the representative household for supplying n_{ij} workers in market j.

Labor supply

Given the distribution of wages and training offers (w_{ij}, t_{ij}); the necessary conditions for household optimality consist of first order conditions at each firm (n_{ij}). Combining these conditions, each firm faces an upward sloping labor supply curve, which can be expressed

[7]Following the human capital specificity context, this is a reasonable assumption. It simply implies that firms within a market require skill bundles that are more similar relative to those of firms in different markets.

[8]As the equilibrium solutions are in relative terms, increasing the disutility of one firm, or reducing the disutility of all the other firms are computationally identical.

by the following inverse labor supply curve[9]:

$$w_{ij} = \left(\frac{n_{ij}}{N_j}\right)^{\frac{1}{\eta}} \left(\frac{N_j}{\mathbf{N}}\right)^{\frac{1}{\theta}} g(t_{ij})^{\frac{1+\eta}{\eta}} G(T_j)^{-\frac{1+\theta}{\theta}} \mathbf{N}^{\frac{1}{\psi}} \tag{1}$$

Interpretation

The micro-foundation of this representative household problem is that there is an exogenous measure H of workers, each of them has idiosyncratic non-monetary preference for working in each market and in each firm, which are drawn from a Fréchet distribution.[10] Those elasticities (η, θ) are the shape parameters of the Fréchet distribution, which are inversely related to the variance of the idiosyncratic preferences. Therefore, if η (or θ) is high, the individual preferences are closer together, each worker has the same idiosyncratic preference regarding each firm (or market). She becomes indifferent on which firm (or market) to work for. This increases the competition between firms, as the wage component is the most important in the worker labor supply decision. On the other hand, if η (or θ) is low, the non-pecuniary preferences are far apart, this reduces the effect of wage in the workers' supply decision. As a worker is more willing to work for a firm with the highest draw of non-pecuniary preference regardless of its wage offer. In other terms, the elasticities (inversely) describe how costly is on average for an "atomistic" worker to move from one market to an another (θ) and to move from different firms within a market (η). In this context, It can be showed that those two specifications (representative household and idiosyncratic utility preferences) are equivalent if the firms do not observe the workers' preferences, but they only know the shape parameters (η, θ) of the preference distribution functions. Although the model could be extended to include two different elasticities for capturing movement across industries or across geographical areas. For the sake of clarity, I consider moving across industries and geographies as equally costly, i.e., for a worker is the same changing industry or location. Therefore, training reduces the moving costs in both directions, even though it should affect only the movement across industries. The extension of the model for capturing these two different channels is left for future research.

[9]See Appendix C for a detailed derivation

[10]A similar framework is proposed by Azkarate-Askasua and Zerecero (2020).

Firms' problem

Given the finite set of employers in a market, the model assumes that the firms compete strategically within a market, but atomistically with respect to the whole economy. This implies that the firms internalize the effect of their labor demand (n_{ij}) and training offers (t_{ij}) on the market-level variables (W_j, N_j, T_j), but they take as given the economy-aggregate wage and labor supply ($\mathbf{W}$, $\mathbf{N}$). In order to maximize profits, firms choose the number of workers to hire (n_{ij}) and how much training to provide (t_{ij}).[11] Contrary to the wage, the training cost (τ) is considered exogeneous and linear in the level of training provided.

Then, a generic firm i in a market j solves the following profit maximization problem,

$$\max_{(n_{ij},t_{ij})} \; z_{ij}(t_{ij}^{1-\gamma} n_{ij}^{\gamma})^{\alpha} - w_{ij}n_{ij} - \tau t_{ij}$$

subject to

$$\begin{cases} w_{ij} = \left(\frac{n_{ij}}{N_j}\right)^{\frac{1}{\eta}} \left(\frac{N_j}{\mathbf{N}}\right)^{\frac{1}{\theta}} g(t_{ij})^{\frac{1+\eta}{\eta}} G(T_j)^{-\frac{1+\theta}{\theta}} \mathbf{N}^{\frac{1}{\psi}} \\ N_j = \left[\sum_{i=1}^{M_j} n_{ij}^{\frac{\eta+1}{\eta}}\right]^{\frac{\eta}{\eta+1}} \end{cases}$$

where z_{ij} denotes the exogenous productivity of firm i.

Partial equilibrium: benchmark case

Consider first the case when training does not affect the labor supply, $G(\cdot) = g(\cdot) = 1$. The first order necessary conditions of the firm profit maximization problem give the following demand for labor and training provisions:

$$\underbrace{\alpha\gamma z_{ij} t_{ij}^{\alpha(1-\gamma)} n_{ij}^{\alpha\gamma-1}}_{\text{Marginal product of labor}=MPL_{ij}} = \underbrace{w_{ij} + \left.\frac{\partial w_{ij}}{\partial n_{ij}}\right|_{n_{(-i)j}} n_{ij}}_{\text{Marginal cost}=MC_{ij}} \tag{2}$$

$$\underbrace{\alpha(1-\gamma) z_{ij} t_{ij}^{\alpha-\alpha\gamma-1} n_{ij}^{\alpha\gamma}}_{\text{Marginal product of training}=MPT_{ij}} = \tau \tag{3}$$

[11] For the sake of simplicity, I assumed that labor and training are the only inputs, but the model can be easily extended to include capital or other additional inputs.

On the one hand, I assume that the firm has a standard demand for training; it takes the price of training as given. On the other hand, given the oligopsonistic framework concerning labor, the firm internalizes the effect of its labor demand on wages; thus, the marginal cost of labor exceeds the wages alone but also accounts for the additional cost associated with increased wages due to an increase in the labor demand. This imperfect competition for labor requires the marginal product of labor to be larger than the wages.

Re-arranging the labor demand condition describes the wages as function of the markdown (μ_{ij}) and the marginal product of labor:

$$w_{ij} = \frac{1}{\mu_{ij}} MPL_{ij} \tag{4}$$

where

$$\mu_{ij}(s_{ij}) = 1 + \varepsilon_{ij}(s_{ij}) = 1 + \frac{\partial log(w_{ij})}{\partial log(n_{ij})} = 1 + \frac{1}{\theta} s_{ij} + (1 - s_{ij}) \frac{1}{\eta} \tag{5}$$

where ϵ_{ij} is the inverse labor supply elasticity of wage; and s_{ij} is akin of the employment share of firm i in market j.[12]

The inverse labor supply elasticity (ϵ_{ij}) depends on the within (η) and across (θ) market substitution elasticities, and the employment-share (s_{ij}). Under the assumption that workers are more willing to change firm than market ($\eta > \theta$), the inverse labor supply elasticity is increasing with the employment share, consequently also the marginal cost of labor. Given this internalized increasing marginal cost with respect to the employment share, relatively larger firms will decide to reduce the number of workers and set wider markdowns. Note that if a firm is monopsonistic ($s_{ij} = 1$), its labor supply elasticity comes exclusively from the across-market substitutability (θ) (inverse labor supply elastiticity is $1/\theta$). On the other hand, if a firm is infinitesimally small ($s_{ij} \to 0$), its labor elasticity is η. The mechanism behind this is that for relatively larger firms is more expensive to hire new workers due to the increasing labor supply curve. Still, at the same time, the higher the returns they extract from the worker productivity through the wage markdown.[13]

[12]Specifically, it is equal to the employer i wage bill share in market j, which, however, is strictly correlated to the employment-share.

[13]Intuitively, a monopsonistic firm can increase its workforce only by attracting workers from other markets, which requires a greater increase in wages to compensate the higher movement costs, but as well firms in other markets to poach its workers have also to compensate for the high movement costs, thus it can offer a relative smaller wage without the threat of losing its employees to other firms. On the other hand, in a

Consider an exogenous rise in the employment concentration (s_{ij}), ceteris paribus. From the inverse labor demand (Equation 4), the markdown increases, consequently, the wages decrease. As in equilibrium, the inverse labor demand must equal the inverse labor supply (Equation 1), the number of workers (n_{ij}) in firm i in market j must decrease.

The effect of an exogenous rise in employment share on the amount of training provided per worker (t_{ij}/n_{ij}) is positive. In contrast, the impact on the total amount of the training provided (t_{ij}) is ambiguous depending on the functional form of the production function.

Re-arrange the labor and training demand conditions

$$\frac{t_{ij}}{n_{ij}} = \left(\frac{1-\gamma}{\gamma}\right)\left(\frac{\mu_{ij}(s_{ij})w_{ij}}{\tau}\right) \tag{6}$$

and consider an exogenous shock to the employment share

$$\left.\frac{\partial(t_{ij}/n_{ij})}{\partial s_{ij}}\right|_{n_{ij},N_j} \propto \frac{\partial \mu_{ij}(s_{ij})}{\partial s_{ij}} > 0 \tag{7}$$

Considering instead the absolute level of training provided,

$$t_{ij} = \left[\frac{\alpha(1-\gamma)^{1-\alpha\gamma}\gamma^{\alpha\gamma}z_{ij}}{\tau^{1-\alpha\gamma}}\right]^{\frac{1}{1-\alpha}} \left[\mu_{ij}(s_{ij})w_{ij}\right]^{\frac{\alpha\gamma}{\alpha-1}} \tag{8}$$

and consider the same exogenous shock to the employment share

$$\left.\frac{\partial t_{ij}}{s_{ij}}\right|_{n_{ij},N_j} \propto \frac{\alpha\gamma}{\alpha-1}\frac{\partial\mu_{ij}(s_{ij})}{\partial s_{ij}} = \begin{cases} \frac{\partial t_{ij}}{s_{ij}} > 0 & \text{if} \quad \alpha > 1 \\ \frac{\partial t_{ij}}{s_{ij}} < 0 & \text{if} \quad \alpha < 1 \end{cases} \tag{9}$$

The mechanism behind these results is that an increase in concentration increases the marginal cost of labor, generating, as a consequence, a substitution effect that induces employers to substitute part of the labor with training, expanding the provision of training per worker accordingly. At the same time, the increase in labor cost also provokes a scale or income effect that goes in the opposite direction. The wage rise leads to a higher total cost, which causes the employer to reduce both inputs. In particular, considering a Cobb-

competitive labor market, firms can more easily poach workers from their competitors, since the movement costs within a market are smaller than across markets.

Douglas production function, the substitution effect dominates the scale effect only when the production function has an increasing return to scale ($\alpha > 1$). Whether an increase in concentration causes an increase in the total amount of employer-provided training depends on which one of the two effects dominates, which is ultimately an empirical question.

Extension: training affects labor supply

Taking the first order condition of the firm profit maximization problem with respect to t_{ij} gives

$$\tau - MPT_{ij} = -\frac{\partial w_{ij}}{\partial t_{ij}} n_{ij} \tag{10}$$

where MPT_{ij} is the marginal productivity of increasing the human capital investment for a firm i in market j. In the case that training does not have any effect on the labor supply, the training provision will satisfy $MPT_{ij} = \tau$. However, including the idea that training affects also the labour supply, there could be either under- or over-provision with respect to the benchmark case. Specifically, it can be shown that

$$-\frac{\partial w_{ij}}{\partial t_{ij}} n_{ij} \propto \left[\frac{1+\theta}{\theta} \varepsilon_{Gt} - \frac{1+\eta}{\eta} \varepsilon_{gt} \right] \tag{11}$$

where

$$\varepsilon_{Gt} = \frac{\partial \log G(T_j)}{\partial \log t_{ij}} \qquad \qquad \varepsilon_{gt} = \frac{\partial \log g(t_{ij})}{\partial \log t_{ij}} \tag{12}$$

The first term within the square parentheses represents the positive "recruiting effect", and the second one the negative "retention effect" associated with training. In this setting, employers can either over or under-provide training depending on whether the two effects dominate the other. Specifically, given labor n_{ij}, whether the elasticity of training on the labor disutility at the market level (ε_{Gt}) dominates the one at the firm level (ε_{gt}) there is over-provision of training as the training cost is higher that its marginal productivity:

$$\frac{1+\theta}{\theta} \varepsilon_{Gt} > \frac{1+\eta}{\eta} \varepsilon_{gt} \;\Rightarrow\; \tau > MPT_{ij}$$

Assuming that the relatively larger an employer in a local labor market, the stronger her impact on the market-level training provision. In this case, although the training returns in terms of productivity are lower than its costs, the employer will bear this higher cost to increase her labor supply. Therefore, this effect on labor supply could boost this incentive for an employer to provide more on-the-job training. In contrast with the benchmark case, employers could increase their total training provisions after an exogenous shock in employer concentration, even when training and labor are not particularly substitutable.

Assuming the firm chooses training provision given their labor demand ($t_{ij}(n_{ij})$), solving the firm profit maximization problem with respect to n_{ij}, gives instead the following first order necessary condition:

$$MPL_{ij} = (1 + \epsilon_{ij})w_{ij} \tag{13}$$

where

$$\epsilon_{ij} = (1 - s_{ij})\frac{1}{\eta} + \frac{1}{\theta}s_{ij} - \left[\frac{1+\theta}{\theta}\varepsilon_{Gt} - \frac{1+\eta}{\eta}\varepsilon_{gt}\right]\varepsilon_{tn} \tag{14}$$

where ϵ_{ij} is the inverse labor supply elasticity of wage; MPL_{ij} is the marginal productivity of labor; s_{ij} is akin of the employment share of firm i in market j; ε_{gt} is the elasticity of the disutility of working for a firm with respect to the level of training provided in that firm; ε_{Gt} is the elasticity of disutility to work in a market given the amount of training provided by the firm; ε_{tn} is the training elasticity of labor. Finally, ϵ^0_{ij} is the inverse labor supply elasticity of wage if there are no training component, as in Equation 5.

Therefore, if the effect of training on the labor supply changes with the level of concentration, ignoring these training effects on the labor supply could lead either to underestimate or overestimate the effect of labor market concentration on wages through the markdown, even after controlling for the amount of training provided (t_{ij}), employer time-invariant productivity (z_{ij}), number of workers (n_{ij}), and labor productivity (MPL_{ij}). In comparison with the benchmark case, there is not a substantial qualitative difference with respect to the effect of concentration on wages. The only difference would be on the interpretation of the direct effect of concentration on the wage markdown.

Market level aggregation

Before moving to the empirical results, to better grasp the relationship between employer concentration, training provision, and wages markdown; I use a specific example for the functions $g(t_{ij})$ and $G(T_j)$, which enable to write the two offsetting effects in a more compact and intuitive form. Specifically, I consider the following functional forms

$$g(t_{ij}) = e^{at_{ij}} \qquad\qquad G(T_j) = e^{bT_j} \tag{15}$$

where a and b are two positive coefficients. Given these functional form, it is possible to derive the elasticities ε_{gt} and ε_{Gt}. Substituting these elasticities in Equation 10 and summing over all the employer i in market j, the market-level over or under-provision of training is

$$\sum_i (\tau - MPT_{ij}) = \frac{1+\theta}{\theta} bHHI_j - \frac{1+\eta}{\eta} a \tag{16}$$

The first term capture the positive "recruiting effect", the second term the negative "retention effect", and HHI_j is the employment Herfindahl-Hirschman index ($\sum_i s_{ij}^2$). In this specific case, the first term dominates the second at a higher concentration level, so we should observe an over-provision in training in a highly concentrated market.

Substituting the elasticities ($\varepsilon_{G,t}, \varepsilon_{g,t}$) in Equation 14 and considering the employees wage market average, the average wage markdown can be approximated as

$$\bar{\mu}_j = 1 + \sum_i s_{ij}\epsilon_{ij} = a + bHHI_j - cT_j HHI_j + dT_j \tag{17}$$

where the Latin letters a to d are positive coefficients. In this specific case, the effect of employer concentration on the wage markdown changes with respect to training. Specifically, without controlling for training, the estimated effect of a change in the HHI on the wages is $b - cT_j$, while controlling also for the training provision, the direct effect of HHI on the wage markdown will be only equal to b. In comparison, in the benchmark case, as training does not affect the labor supply, the coefficients c and d should be equal to 0.

3 Data

To test the empirical predictions obtained in Section 2, I exploit two main data sources: the Italian Orbis dataset and the *Rilevazione longitudinale su Imprese e Lavoro* (RIL).

3.1 Employer Concentration

To measure the level of employer concentration across local labor markets, I use the Italian ORBIS dataset, AIDA (*Analisi Informatizzata Delle Aziende*), from 2013 and 2018. Maintained by Bureau van Dijk, the AIDA database contains Italian firms' balance sheets and income statements.[14] Among many other variables, the dataset gathers information on the number of employees, location, industry classification (NACE[15]), revenues, wage bill, and value-added. From this database, I get the measures of employment concentration, value-added per worker, and wages (defined as wagebill per worker).

Following a similar procedure detailed in Kalemli-Ozcan et al. (2015) and Gopinath et al. (2017), I drop firm-year observations that have missing information regarding their industry and location of activity, as well as those firm-year observations with missing, zero, or negative values for wage bill and employment. I also winsorize at the 1 and the 99 percentile variables such as value added and wage bill.

3.1.1 Labor Market Herfindahl-Hirschman Index

As standard, I measure employer concentration on the basis of the Herfindahl-Hirschman Index (HHI), defined as the sum of squares of each firm's employment shares in a local labour market. Specifically,

$$HHI_{mt} = \sum_{j=1}^{N} \left(\frac{e_{jmt}}{\sum_{k=1}^{N} e_{kmt}} \right)^2 \tag{18}$$

[14] In the following, I use the terms employer and firm interchangeably, in both case I consider the group of establishments/plants own by the same company identified by a tax code (*codice fiscale*). In Italy, however, the large majority of the firms has a unique establishment.

[15] The NACE (Nomenclature statistique des activités économiques dans la Communauté européenne is the industry standard classification system used in the European Union, analogous to the NAICS in the USA. In Italy takes also the name of ATECO (ATtività ECOnomiche).

where e_{jmt} denotes the number of workers employed by employer j in local labor market m and year t. The use of concentration indices necessitates an appropriate definition of labor market. Following the literature, I define a local labor market as a combination between an industry and a geographical area.[16] As baseline specification, I consider a local labor market as a combination between a 3-digit NACE industry class and a NUTS level 2 region.[17]

Table 1 reports the summary statistics. It shows the HHI distribution, the average yearly wages, and the value added on the final sample. To illustrate in greater detail the HHI distribution, the histograms in Figure 1 present the distributions of HHI across employers, workers,and local labor markets. As observed by previous papers in different contexts, the average market is highly concentrated, but the average worker or firm is moderate concentrated. While, Figure F8 maps the HHI weighted by the number of workers at each industry aggregated at the NUTS 2 or 3 level.

Alternative Concentration Indexes

To test the sensitivity of the HHI measure of concentration, I further consider different concentration measures, such as the wage-bill concentration (WB-HHI) and the 3-Subject Concentration Ratio (CR3), defined as followed:

$$WB\text{-}HHI_{mt} := \sum_{j=1}^{N} \left(\frac{w_{jmt}}{\sum_{k=1}^{N} w_{kmt}} \right)^2$$

$$CR3_{mt} := \sum_{q \in Top3_{mt}} \frac{e_{qmt}}{\sum_{k=1}^{N} e_{kmt}}$$

where w_{jmt} is the wage bill of employer j, in market m, and year t; while q identifies the three largest employer in market m and year t. However, as it can be seen in Figure F8, these three concentration indexes are highly correlated.

[16] See for example Rinz (2022); Lipsius (2018); Abel et al. (2018); Benmelech et al. (2020); Popp (2021); Berger et al. (2022). An alternative procedure is to consider occupations rather than industries. However, there is little practical difference in term of concentration using the two different procedure, as showed for example by Handwerker and Dey (2018) in the USA.

[17] The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system for dividing up the economic territory adopted by the EU and the UK. For clarity, I consider the Italian classification in *Regioni* rather than the EU NUTS level 2 classification of Italy. The EU NUTS 2 partially differ from the Italian region classification with respect to the *Regione Autonoma Trentino-Alto Adige/Südtirol*, as the EU NUTS level 2 differentiates between the two autonomous provinces of Trento and Bolzano. Therefore, although Italy has 20 regions, it has 21 NUTS level 2 units. Despite the fact that I consider the Italian classification of regions, I misuse the term NUTS 2 for clarity to those readers unfamiliar with the Italian territorial subdivision.

3.2 Training Data

The RIL surveys of 2015 and 2018 contain detailed information on firms' investment in training, as well as other relevant characteristics such as the number of employees, location (NUTS level 2), and industry (NACE 3 digit). Maintained by the Italian National Institute for the Analysis of Public Policies (INAPP), each survey is conducted on a sample of around 30 thousand firms, representative of the universe of private extra-agricultural Italian firms. Around half of the firms are interviewed in both years, which gives the RIL a panel structure. Most importantly, the RIL focuses on the demand side of the labor market (i.e., firms), while most training datasets provide information only on the supply side (workers). In particular, besides the number of workers receiving training, it also lists the amount of monetary resources invested in training by the employer.[18]

For the purpose of the analysis, I have restricted the analysis to only those firms with at least 2 employees and not missing information regarding industry classification and location. I winsorize the amount invested in training at the 99 percentile. Given the partial panel structure of the RIL dataset, I have constructed two different sample. The first ignores the panel scheme structure and consider the two surveys as a repeated cross section. The second instead focus exclusively on the firms that are interviewed in both surveys. Table 2 report the summary statistics associated with these two samples. Figure 2 shows the average amount of employer-provided training per worker and the average total amount invested across NUTS 2 regions, as well as the average number of employer providing training. Figure 3 displays the average training outcomes across 1 digit NACE industries.

4 Empirical strategy

The theory in Section 2 suggests that employer concentration should cause (i) a negative effect on wages, (ii) a positive effect on training, and (iii) an a decreasing returns of training investment in terms of firm value added per worker. The empirical approaches to test these predictions are described respectively in Sections 4.1, 4.2, and 4.3.

To account for possible endogeneity, I develop an instrumental strategy for the HHI index,

[18] Among recent papers using the same dataset, see Bratti et al. (2021) and Berton et al. (2018). More details are instead available at https://inapp.org/it/dati/ril.

detail further in Section 4.4

4.1 Effect of Employer Concentration on Wages

I estimate the effect of employer concentration on wages both at the market and employer level using the full AIDA dataset from 2013 to 2018. Specifically, I rely on the following specification:

$$\log(w_{jmt}) = \beta \log(HHI_{mt}) + \alpha X_{jmt} + \text{fixed effects} + \varepsilon_{jmt} \tag{19}$$

where subscripts j, m, and t denotes, respectively, employer, local labor market, and year; $\log(w_{jmt})$ is the natural logarithm of the average wages in firm j, market m, and year t; X_{jmt} includes time-varying controls at the firm or market level, such as number of employees, unemployment level. The fixed effects are different sets of dummies that may include year, employer, industry, region fixed effects.

The fixed effects play the role to disentangle the effects of both observable and unobservable characteristics that could threaten the identification. Specifically, it is important to control for employer fixed effects as to control for all time-invariant employer characteristics that could determine, at the same time, the decision to locate into a specific local labor market and its productivity. The concern is that, if high-productivity employers self-select into high concentration markets, without employer fixed effects one would observe a spurious positive association even in the absence of a causal relationship between wages and labor market concentration. Clearly, it remains the threat arising from time-varying market characteristics, which I further described in Section 4.4.

4.2 Effect of Employer Concentration on Employer Provided Training

To estimate how employer concentration affects the employer provided training investment, I match each RIL firm with the corresponding local labor market computed from the AIDA dataset, and estimate the following econometric model:

$$Y_{jmt} = \beta \log(HHI_{mt}) + \alpha X_{jmt} + \text{fixed effects} + \varepsilon_{jmt} \tag{20}$$

where subscript j, m, and t indicate as in Equation 19 firm, market, and year. Y_{jmt} is the outcome variable, which can be (i) the inverse hyperbolic sine function (IHS) of the total amount of euro invested by the employer in training, (ii) the IHS of the amount of euro invested per number of workers, (iii) a binary variable on whether the employer has provided any training.[19]

4.3 Effect of Employer Concentration and Training on Productivity and Wages

Unfortunately, the RIL dataset does not provide information on firm performance, for this reason to investigate (i) whether the return of training in term of worker's productivity decreases with employer concentration and (ii) how the effects of employer concentration on wages changes when the impact of HHI on training investment is taken in account, I compute the market level averages of employer provided training investment per worker and probability, as well as the market level average wages and labor productivity, the latter is measured as value-added per worker.

To study how the return of training investment in term of labor productivity changes with the HHI, I estimate the following regression model:

$$log(Y_{mt}) = \beta \log(HHI_{mt}) \times IHS(T_{mt}) + \gamma IHS(T_{mt}) + \alpha X_{mt} + \text{fixed effects} + \varepsilon_{mt} \tag{21}$$

where Y_{mt} denotes the labor productivity, and $IHS(T_{mt})$ is the inverse hyperbolic sine transformation of the market average of either the training probability or the amount of Euro per employees invested by the employers for the training of workers.

Given Equation 21, the estimated labor productivity elasticity on employer provided training investment reads as follow:

$$Elasticity_{Y,T} := \frac{\partial log(Y_{mt})}{\partial IHS(T_{mt})} = \hat{\gamma} + \hat{\beta} log(HHI_{mt}) \tag{22}$$

In this case, β is estimated instrumenting the interacted term ($\log(HHI_{mt}) \times IHS(T_{mt})$)

[19] The inverse hyperbolic sine function is defined as $IHS(x) = log(x + \sqrt{x^2 + 1})$. Given the presence of outliers and several firms which do not provide training, the benefit of IHS is that it can also transforms these null values, contrary to log transformations.

with the interaction between $IHS(T_{mt})$ and the instrument of $log(HHI_{mt})$ as described in Section 4.4.

The empirical model to test the effects on wages is as follows

$$log(W_{mt}) = \beta_1 log(HHI_{mt}) + \alpha X_{mt} + \text{fixed effects} + \varepsilon_{mt} \tag{23}$$

$$log(W_{mt}) = \beta_2 log(HHI_{mt}) + \gamma IHS(T_{mt}) + \alpha X_{mt} + \text{fixed effects} + \varepsilon_{mt} \tag{24}$$

where W_{mt} denotes the market level wages, and $IHS(T_{mt})$ is the inverse hyperbolic sine transformation of the market average of either the training probability or the amount of Euro per employees invested by the employers for the training of workers.

As aforementioned, the training variables are at the market level, so β does not characterize exactly the treatment effect, but it can be interpreted as an intention-to-treat effect. It assumes that employers in markets with higher average training investments are likelier to invest in training, however it can not be actually observed who are those employers that are actually training.

To estimate β_1 and β_2, I rely on the standard instrumental variable approach described in Section 4.4. On the other hand, the identification strategy for γ relies on the assumption that training investment decisions are unaffected by time-variant unobserved variables after controlling for market level controls, employer concentration, and fixed effects.

Assuming the parameters of interest γ and β_2 are correctly identified, the difference between β_1 and β_2 assesses the indirect effect of HHI on wages through training. In other words, the potential downward bias on the wage markdown arising from neglecting the effect of concentration on employer provided training, and the effect of the latter on labor productivity.

4.4 Endogeneity Threat

As for any non-experimental analysis, concerns arise about endogeneity. The primary threat of the identification strategy is the occurrence of market-specific shocks that affect both concentration, wages, and training. For example, the rising of productive firms could increase concentration and increase both training investments and wages. On the other hand, an increase in concentration could also be driven by the worsening of business conditions in a local labor market, through firms failing and mass workers layoff. This will likely cause a reduction in both wages and training investments. Therefore, although there is an issue about the endogeneity of the concentration measure, the bias can go in both directions.

To address this issue, I use a so-called Hausman-Nevo instrument (see Hausman (1996) and Nevo (2001)). Specifically, I instrument the variation in a local market concentration with the average of the inverse of the number of employers in the same industry but in other geographical areas.

$$log(HHI^{instr.})_{mt} = \frac{1}{M-1} \sum_{k \neq m} -log \left(\sum_{j} \mathbb{1}(e_{jmt} > 0) \right) \tag{25}$$

where M is the number of geographical areas, t is the year, m is an industry, and e_{jmt} identifies the number of employees.

Conceptually, this IV strategy identifies the effects of local concentration on wages and training using only the variation of the local concentration due to global forces and not market-specific ones. A similar instrumental approach was already applied in a similar context by Martins (2018); Qiu and Sojourner (2019); Azar et al. (2020a); Marinescu et al. (2021); Bassanini et al. (2021).

A possible concern remains that national industry trends in concentration may be correlated with unobservable national trends in industry productivity, demand, or supply, which could confound the estimates. In this regards, I further control for labor market measures such as the local labor market unemployment rate and the total employment.

As a final concern, since labor market concentration is correlated with product market concentration, the observed effects could emerge from the latter rather than the former.[20] To address this issue, I further control for market level product concentration, which I define as the sum of the squares of the national revenues shares in a local labor market.

[20] For example, Böckerman and Maliranta (2012); Bilanakos et al. (2017); Autor et al. (2020) find empirical evidence that product market concentration positively affect employer-provided training or other tools to improve worker productivity.

4.4.1 Additional instrumental variable approach

I test the robustness of the results considering an additional instrument develop through a "double" Bartik design, similar to Schubert et al. (2020) and Chodorow-Reich and Wieland (2020). A variation in the employer concentration for industry i, region r, and year t can be decomposed as a function of the previous employment share of each firm j ($s_{j,i,r,t-1}$) and the employment growth rate for each firm ($g_{j,i,r,t}$) with respect to the market growth rate ($g_{i,r,t}$). Specifically,

$$\Delta HHI_{i,r,t} = \sum_j s^2_{j,i,r,t} - \sum_j s^2_{j,i,r,t-1} = \sum_j s^2_{j,i,r,t-1} \left(\frac{(1+g_{j,i,r,t})^2}{(1+g_{i,r,t})^2} - 1 \right)$$

Following Bartik strategy, I further decompose the NACE 3digit code into 4 digit code, and I instrument the employment growth for each firm j in sub-industry k belonging to industry i and region m with the average national employment growth of sub-industry k, leaving out the region m. Formally, the instrument is as follow:

$$Z^{HHI}_{i,r,t} = log \left\{ \sum_j s^2_{j,i,r,t-1} \left[\frac{(1+\tilde{g}_{j,k(i),-r,t})^2}{(1+\tilde{g}_{i,r,t})^2} - 1 \right] \right\} \tag{26}$$

where $\tilde{g}_{j,k(i),-r,t}$ is the national growth in employment in year t for the sub-industry k of which firm j belongs, leaving out the region r; $\tilde{g}_{i,r,t}$ is the predicted employment growth rate for industry i and region r as predicted from $\tilde{g}_{j,i,r,t}$, i.e. $\tilde{g}_{i,r,t} = \sum_j s_{j,i,r,t-1}\tilde{g}_{j,i,r,t}$.

To avoid that thee results are driven by relative small sub-industry that can be affected by particular shocks, in computing the predicted employment growth I consider only those sub-industry that are present in at least five NUTS level 2 regions. This leads to the fact that the employment shares of sub-industries do not sum to one. To address this issue, following Schubert et al. (2020) and Borusyak et al. (2022), I add an "exposure control", defined as the sum of the squared employment shares of the sub-industry used in constructing the instrument. A more concerning threat derives from the fact that in the model firm's employment growth should affect training and wages through employer concentration, which is a quadratic term. However, it is very likely that firm's growth have also a linear effect on local labor demand, training decisions and productivity. I address this issue by following Schubert et al. (2020) including two additional controls: (i) the actual employment growth rate in industry i and region r ($g_{i,r,t}$) and (ii) the predicted employment growth rate ($\tilde{g}_{i,r,t}$). This conceptually should capture the potential direct linear effects of firms' employment growth on labor demand, training, and productivity.

Overall, despite the relative caveats of both approaches, the rationale is that by combining their relative strengths to provide a more robust picture of the effects of employer concentration on wages and training.

5 Results

This section shows the main results on the effects of employer concentration on wages, subsection 5.1, on employer provided training investment, subsection 5.2, and on the combined effect on wages and productivity, subsection 5.3.

5.1 Effects on wages

Following Equations 19 and 25, I estimate the impact of employer concentration on firm's mean yearly wages. Results are shown in Table 3. Columns 1 and 2 report the basic OLS estimates considering two different specifications of fixed effects: Column 1 considers year and employer fixed effects, Column 2 uses year times NUTS 2 region and year times NACE 3 industry fixed effects. Columns 3 and 4 adopt the instrumental variable approach described in Section 4.4 and use the same different specifications in terms of fixed effects of Columns 1 and 2.

The results presented are in line with the basic predictions of the theory. Across all four specifications, the effect of employer concentration on wages is negative and statistically significant. However, magnitudes vary across the different specifications. The elasticity of wages on employer concentration ranges from -0.06 to -0.18. This implies that an increase in HHI by 10 percent decreases average yearly wages by 0.7 to 1.8 percent. It is worth noticing that the IV estimates are drastically larger in magnitude, suggesting that some combination of omitted variable bias or measurement error biases the coefficient toward zero in the simple OLS regressions.[21] At the same time, the estimates considering

[21] The F-statistics are high and well above the rule of thumb thresholds. The first stage is shown in Table T2.

employer fixed effects are also drastically larger underlying the importance to control for all time-invariant firm characteristics.

5.1.1 Robustness and sensitivity

To test the sensitivity of the effects on wages to different definitions of local labor market, Table T1 reports the results of the IV specification with employer and year fixed effects, analogous to Column 3 of Table 3, with different market specifications. Specifically, Panel A considers NUTS level 2 (Italian ”regioni”) as the geographical definition as in Table T1, while Panel B considers NUTS level 3 (Italian ”province”). While the columns defines the digit of the NACE industry classifications. The instrumental variable approach is as described in Section 4.4 adjusted for the different specifications of a local labor markets. It can be seen how the results are robust to the different definitions of a local labor market getting in general larger in magnitude as the local labor market gets finer.

Figure 4 tests the sensitivity of the results to different measures of concentration. Specifically, (i) log. HHI consider the preferred definition described as the log. employment Herfindahl-Hirschman index; (ii) log. WB-HHI is the log. wage-bill Herfindahl-Hirschman index, i.e., the sum of squares of wage-bill share rather than employment shares; and (iii) the log. CR3 is the log. of the employment concentration ratio of the three largest employers in a local labor market, i.e., the sum of the employment shares of these three largest firms. For all the three different indexes, I also add the controls for the log. of the number of employees in the firm, the log. of the total number of employees in the local labor market, and the log. of the unemployment rate at the NUTS level 2 region. All the specifications includes employer and year fixed effects.

As an additional robustness test, Figure 5 explores the robustness of the results including the NUTS level 2 log. unemployment rate and the local labor market total employment for each market-year observation. It further compare the estimates of our preferred instrumental variable approach and the Bartik instrument described in Section 4.4.1. Also in these cases, the negative and significant relation between employer concentration and wages holds. All the specifications include employer and year fixed effects.

Finally, Table T5 shows the results when controlling for the product market concentration. The results are in line with what reported in Table 3, specifically, in the preferred specification with year and employer fixed effects, the effect of employer concentration on wages is even slightly larger.[22]

5.2 Effects on employer provided training

In this section, I investigate how employer concentration affects employer provided training. Specifically, I implement the specification delineated in Equation 20, with as outcome variables: (i) a dummy variable denoting whether an employer has invested in training, (ii) the inverse hyperbolic sine transformation (IHS) of the amount invested in training in total and (iii) per worker.[23]

Table 4 reports the results on the training dummy, considering the RIL as a cross-section repeated sample. Columns 1 reports the basic OLS estimates and Column 2 controls for the log. of the number of employees in that firm. The coefficients associated with employer concentration are positive and statistically significant in both specifications, indicating that higher employer concentration is associated with more employer provided training. Next, Column 3 and 4 reports the TSLS estimations.[24] Once again, the estimates are positive and statistically significant. The effects is also larger than in the basic OLS specification: considering Column 4, an increase in HHI by 10 percent makes firms 0.6 percentage points more likely to invest in training, which with respect to the mean constitutes 1 percent increase in the training probability. Alternatively, moving from the 25 percentile to the 75 percentile of the HHI distribution increases the training probability by around 10 percentage points.[25]

In Table 5, I exploit the panel structure of the RIL dataset by limiting the analysis on only those firms available in both surveys and including employer fixed. The results are in line with Table 4 but becomes slightly smaller in magnitude.

[22] In this regressions, I am not instrumenting the product market concentration, despite it is also likely endogeneous. This because I am not interested in correctly estimating the effect of product market concentration, but rather to disentangle its potential effect on the estimates of employer concentration.

[23] I use the inverse hyperbolic sine transformation because there are many zero-valued observations, as most of the employers do not provide any training. The strength of the IHS transformation is that it behaves approximately identically to a logarithmic transformation, yet it allows retaining zero-valued observations. The IHS transformation is computed as follow: $IHS(X) = log(x + \sqrt{x^2+1})$

[24] The first stage is reported in Table T3.

[25] In a lin-log probability model, for every 10 percentage increase in the independent variable, the dependent variable increases by about $[\hat{\beta} \times log(1.1)] \times 100$ percentage points. The interquartile change is computed: $\hat{\beta} \times log[\frac{p75(HHI)-p25(HHI)}{p25(HHI)} + 1]$; where $p25(HHI) = 70$ and $p75(HHI) = 434$, as reported in Table 2.

Moving on the intensive margin, Tables 6 and 7 display the effects of employer concentration on the amount of Euro invested in training by an employer per worker in the cross-section and panel RIL dataset, respectively. The coefficients are positive and statistically significant in all the different specifications at least at 10% significance level. Specifically, in the preferred specification (Table 7, Column 4) that includes employer fixed effects and control for the number of employees, the estimated elasticity of training investment with respect to employer concentration is 0.27, which implies that an increase in HHI by 10 percent raises employer training investment per worker by around 2.7 percent.[26]

Finally, Tables 8 and 9 replicate the analysis in Tables 6 and 7, where the dependent variable is the total amount of Euro invested in training by the employer. Table 8 accounts for the entire sample. Table 9 focuses on the panel sample. The results are in line with those on the investment per workers, yet slightly less significant.

5.2.1 Robustness and sensitivity

Unfortunately, the RIL dataset do not provide finer definitions for industry and region, therefore, I cannot test the sensitivity to different measure of local labor market concentration. As done in 5.1.1, Figure 6 shows the robustness of the preferred specification results for all the three outcome variables to the inclusion the additional controls for the log. unemployment rate at the NUTS level 2 region and the local labor market total employment, as well as to different concentration indexes. The results are robust, the effects become even larger with the inclusion of market level controls in all the different specifications and across the different concentration indexes.

Figure 7 compares the TSLS results using the baseline Hausmann instrument (eq.25) and the Bartik instrument (eq.26) on the three training outcomes. The Bartik instrument obtains even larger positive effects of employer concentration on employer provided training.[27]

Finally, the results are also robust to the control for product market concentration, Tables T6, T7, and T8 report the results with respect to employer-provided training probability, training investment per worker, and total training investment, respectively.

[26]Technically, this is an approximation as it is not a log-log model, but a log-IHS model. However, it can be showed that the latter is approximately identical to the former when the mean of the non-transformed independent variable is larger than 10 as a rule of thumb, see Bellemare and Wichman (2020) or Appendix D.

[27]The first stage using the IV-B is reported in Table T4.

5.3 Combined Effects on Productivity and Wages

To explore the impact of employer concentration and training investments on workers productivity, as depicted in Section 4.3.

Table 10 estimates Equation 21, considering the impact of the average market training investment per worker, HHI, and their interaction on the log. value-added per worker. I instrument HHI with the standard instrument defined in Equation 25 and the interaction between HHI and average training with the interaction between the market average training investment and the HHI instrument. Columns 1 and 2 display the OLS estimates, while Columns 3 and 4 the TSLS estimates. Across all four specifications, the regressions shows that an increase in the mean market training increases the value-added per worker, moreover it also shows that this positive impact of the average training investment per worker decreases with the employer concentration. Considering Column (4) and a market with HHI close to zero[28], the elasticity of labor productivity to market average training is around 0.16. However, this elasticity decreases at rise of the HHI, considering an inter-quartile range change in log HHI from 2, i.e. moving from 4 to 6, the elasticity of labor productivity to training goes from 0.07 to 0.02.[29] Figure 8 illustrates this decreasing elasticity with respect to employer concentration.

Table 11 replicates the previous estimation specification, using as outcome variable the inverse hyperbolic transformation of the market level training probability. The regressions shows a positive and significant effect of training on labor productivity, and as before the positive returns of training on labor productivity decreases with local labor market concentration. With regard to Column (4) and a log. HHI close to zero, a one percent rise in the market IHS of training probability increases the value-added per worker of around 0.7 percent. As before, this labor productivity elasticity is decreasing with the HHI. To give an example, given the same inter-quartile change in HHI, moving from a log. HHI of 4 to 6, the elasticity reduces from 0.3 to 0.1.

I now consider how the wage elasticity of employer concentration changes when controlling for training, I implement the two-step specification, following Equations 23 and 24.

[28]Remember that the log HHI is computed on the HHI times 10,000, therefore a log HHI close to zero implies an HHI close to zero too.

[29]Interestingly, the coefficients of HHI are positive and significant. A possible justification can be extracted from the model in Section 2. As firms are identical except for their productivity, for generate high level of concentration, there should be a few very productive firms.

Table 12 reports the effects of employer concentration on wages when controlling for employer provided training at the market level. Although non statistically significant, the inclusion of market level training variables increases the wage elasticity to employer concentration of around 0.1 or 0.2 percentage points, which consists in a 1 or 2 percent rise in magnitude. The coefficient of the training market average are also all positive and statistically significant, suggesting that workers seen at least in part a return in term of increase in wages from training. However, the effect are particularly small in magnitude. Moving from the 25 percentile to the 75 percentile in term of employer provided training investment per worker, i.e. from 0 to 46 euro, the market average yearly wages increases by around 1.6 log points.[30]

Overall, even if not conclusive, these findings support the empirical predictions of the model in Section 2. On the one hand, the effect of training on labor productivity is generally positive but decreases with employer concentration. As labor market concentration rises, the relative importance of the labor supply component of training increases: employers exploit on-the-job training to increase their labor supply. On the other hand, controlling for the effect of concentration on training increases in magnitude the negative effect of concentration on wages. As employers invest more in training with the rise in HHI, neglecting this effect tends to underestimate employers' markdown on wages. However, this last result seems relatively small in size. Ultimately, the impossibility of linking firm performance to training data makes a precise estimate of the findings unfeasible, which is left for future research.

6 Conclusions

What are the effects of employer concentration on wages and employer provided training? By exploiting administrative Italian data, I showed that employer concentration decreases wages, in line with the olipsonistic theoretical literature. However, more interestingly, I document how not only the wages changes, but also the employer investments in training. Specifically, I show that employers in a highly concentrated labour market increase training provision both at the extensive and intensive margin: a 10 percent increase in HHI makes employers 1 percent more likely to provide any form of training and increases by 3 percent the monetary resources invested in training per worker. I also observe heterogeneity in the

[30]Calculated as $(IHS(46) - IHS(0)) \times 0.0036 = 0.0163$.

returns of training investment on worker productivity. The impact of training investment on labor productivity decreases with employer concentration, suggesting that employer in high concentrated market are more prone to invest in training even if the investment has a lower return in productivity. Moreover, the combined effect of concentration on wages and training provision lead to a direct corollary that employer concentration effects on wages could be larger than what previously estimated. Ignoring that a rise in concentration increases training provisions, which in turn increases worker productivity, could downward bias the estimates of employer concentration on wages. Unfortunately, the survey data do not have detailed information on firm performance, thus, although the findings seem to support this idea, the outcome is inconclusive and left for future research.

To conclude, the paper directly speaks to policymakers as we document the multifaceted effects of employer concentration on wages and on-the-job training. The results show that the training behaviour of employers differs in concentrated markets and should be taken into consideration when designing anti-trust policies aimed at mitigating anti-competitive practice as well as for active labor market policies aimed at bridging the skill gap of displaced workers.

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List of Tables

Table 1: Summary statistics: Wages and Employer concentration, full sample

	N	mean	sd	p25	median	p75	p90
avg. yearly wages	2,691,810	21,048	24,671	11,221	18,959	26,610	35,064
HHI$\times$10k	2,691,810	441	886	63	161	420	1,001
log(HHI$\times$10k)	2,691,810	5.12	1.36	4.14	5.08	6.04	6.91
value added per worker	2,691,810	41,361	106,974	7,821	28,988	50,034	79,558
value added over wagebill	2,691,810	2.35	11.7	1.08	1.67	2.26	3.61
value added	2,691,810	462,021	1,118,816	18,609	111,912	371,824	1,045,751
				Market level			
HHI$\times$10k	29,911	3,057	3,214	573	1,700	4,560	10,000
log(HHI$\times$10k)	29,911	7.3	1.39	6.35	7.44	8.43	9.21

Notes: This table reports summary statistics from the ORBIS dataset. It provides information on the average yearly wages paid by an employer, employment concentration (HHI), as well as on value added, valued added per worker, and valued added over wagebill. *Market level* refers to data at the local labor market level, i.e. a combination between a NUTS level 2, NACE 3-digit industry class, and a year.

Table 2: Summary statistics: RIL dataset

	N	mean	sd	p25	median	p75	p90
PANEL A: *RIL Cross-section dataset*							
Training dummy	48,046	.58	.45	0	1	1	1
Cost training	48,046	1,595	9,876	0	0	300	2,300
Cost training per worker	48,046	97	278	0	0	46	275
HHI×10k	48,046	444	856	70	165	434	1,048
log(HHI×10k)	48,046	5.2	1.3	4.2	5.1	6.1	7
PANEL B: *RIL Panel dataset*							
Training dummy	20,686	.62	.47	0	1	1	1
Cost training	20,686	2,259	12,338	0	0	500	3,000
Cost training per worker	20,686	102	271	0	0	80	290
HHI×10k	20,686	450	877	65	161	436	1,075
log(HHI×10k)	20,686	5.2	1.3	4.2	5.1	6.1	7

Notes: This table reports summary statistics from the matched RIL and ORBIS datasets. It includes all those employers interviewed in the RIL surveys (2015,2018). It provides information on whether an employer has provided training (*Training dummy*), the monetary resources invested by each employer in workers training (*cost training*), and the average investment per worker (*cost training per worker*) as well as the employer concentration HHI computed from the ORBIS dataset. Panel A includes all those employers interviewed in either the RIL survey 2015 or 2018. While, Panel B includes only those employers that were interviewed in both surveys.

Table 3: Wage elasticities of employer concentration

	OLS		IV	
	(1)	(2)	(3)	(4)
log. HHI	-0.0063***	-0.0160***	-0.1799***	-0.0678***
	(0.0012)	(0.0007)	(0.0074)	(0.0037)
Year	✓		✓	
Employer	✓		✓	
Year×Region		✓		✓
Year×Industry		✓		✓
MDV	9.707	9.669	9.707	9.669
mean(HHI)	441.700	440.714	441.446	440.629
std(log(HHI))	1.364	1.365	1.364	1.365
N	2,591,927	2,691,763	2,591,777	2,691,663
R^2	0.704	0.138	.	.
F	.	.	30,687	1,578

Notes: The dataset consists in the AIDA dataset and it is at the employer-year level. The table reports the OLS and TSLS regression outputs using as dependent variables the log. average wages for each employer. The independent variable is the log of the employment HHI, measured at a combination between an industry (NACE 3 digits) a NUTS level 2 Region, and a year. The instrumental variable consists to the log inverse number of firms across local labor markets, as described in section 4.4. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 4: Effects on training probability: RIL cross-section

	OLS		IV	
	(1)	(2)	(3)	(4)
log. HHI	0.0093***	0.0105***	0.0465***	0.0586***
	(0.0031)	(0.0030)	(0.0150)	(0.0145)
log. employees		0.1270***		0.1273***
		(0.0024)		(0.0024)
Year×Region	✓	✓	✓	✓
Year×Industry	✓	✓	✓	✓
MDV	.578	.578	.578	.578
mean(HHI)	737.694	737.694	736.745	736.745
std(log(HHI))	1.363	1.363	1.363	1.363
N	48,020	48,020	48,014	48,014
R^2	0.135	0.185	.	.
F	.	.	2,117	2,115

Notes: The dataset consists in the cross-section RIL and it is at the employer-year level. The table reports the OLS and TSLS regression outputs using as dependent variables the training dummy, which is equal to 1 if the employer has invested in training. The independent variable is the log of the employment HHI, measured at a combination between an industry (NACE 3 digits) a NUTS level 2 Region, and a year. The instrumental variable consists to the log inverse number of firms across local labor markets, as described in section 4.4. "log. employees" is a control for the log. of the number of employees in each firm. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors, in parentheses. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 5: Effects on training probability: RIL panel

	OLS		IV	
	(1)	(2)	(3)	(4)
log. HHI	0.0415***	0.0414***	0.0399***	0.0412***
	(0.0072)	(0.0072)	(0.0123)	(0.0123)
log. employees		0.1270***		0.1270***
		(0.0124)		(0.0124)
Year	✓	✓	✓	✓
Employer	✓	✓	✓	✓
MDV	.624	.624	.624	.624
mean(HHI)	749.400	749.400	745.732	745.732
std(log(HHI))	1.370	1.370	1.368	1.368
N	20,686	20,686	20,676	20,676
R^2	0.721	0.724	.	.
F	.	.	5,419	5,420

Notes: The dataset consists in the panel RIL and it is at the employer-year level. The table reports the OLS and TSLS regression outputs using as dependent variables the training dummy, which is equal to 1 if the employer has invested in training. The independent variable is the log of the employment HHI, measured at a combination between an industry (NACE 3 digits) a NUTS level 2 Region, and a year. The instrumental variable consists to the log inverse number of firms across local labor markets, as described in section 4.4. ”log. employees” is a control for the log. of the number of employees in each firm. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors, in parentheses. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 6: Effects on employer investment in training per worker: RIL cross-section

	OLS		IV	
	(1)	(2)	(3)	(4)
log. HHI	0.0301*	0.0350**	0.1493*	0.1972**
	(0.0173)	(0.0170)	(0.0836)	(0.0825)
log. employees		0.5005***		0.5015***
		(0.0134)		(0.0134)
Year×Region	✓	✓	✓	✓
Year×Industry	✓	✓	✓	✓
MDV	2.29	2.29	2.29	2.29
mean(HHI)	737.694	737.694	736.745	736.745
std(log(HHI))	1.363	1.363	1.363	1.363
N	48,020	48,020	48,014	48,014
R^2	0.113	0.139	.	.
F	.	.	2,117	2,115

Notes: The dataset consists in the cross-section RIL and it is at the employer-year level. The table reports the OLS and TSLS regression outputs using as dependent variables the inverse hyperbolic sine transformation of the employer investment in training per worker. The independent variable is the log of the employment HHI, measured at a combination between an industry (NACE 3 digits) a NUTS level 2 Region, and a year. The instrumental variable consists to the log inverse number of firms across local labor markets, as described in section 4.4. ”log. employees” is a control for the log. of the number of employees in each firm. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors, in parentheses. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 7: Effects on employer investment in training per worker: RIL panel

	OLS		IV	
	(1)	(2)	(3)	(4)
log. HHI	0.1375***	0.1372***	0.2603***	0.2650***
	(0.0426)	(0.0425)	(0.0727)	(0.0726)
log. employees		0.4510***		0.4511***
		(0.0735)		(0.0735)
Year	✓	✓	✓	✓
Employer	✓	✓	✓	✓
MDV	2.61	2.61	2.61	2.61
mean(HHI)	749.400	749.400	745.732	745.732
std(log(HHI))	1.370	1.370	1.368	1.368
N	20,686	20,686	20,676	20,676
R^2	0.694	0.695	.	.
F	.	.	5,419	5,420

Notes: The dataset consists in the panel RIL and it is at the employer-year level. The table reports the OLS and TSLS regression outputs using as dependent variables the inverse hyperbolic sine transformation of the employer investment in training per worker. The independent variable is the log of the employment HHI, measured at a combination between an industry (NACE 3 digits) a NUTS level 2 Region, and a year. The instrumental variable consists to the log inverse number of firms across local labor markets, as described in section 4.4. "log. employees" is a control for the log. of the number of employees in each firm. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors, in parentheses. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 8: Effects on employer total investment in training: RIL cross-section

	OLS		IV	
	(1)	(2)	(3)	(4)
log. HHI	0.0240	0.0346	0.1136	0.2160**
	(0.0233)	(0.0225)	(0.1130)	(0.1090)
log. employees		1.0707***		1.0718***
		(0.0177)		(0.0177)
Year×Region	✓	✓	✓	✓
Year×Industry	✓	✓	✓	✓
MDV	3.63	3.63	3.63	3.63
mean(HHI)	737.694	737.694	736.745	736.745
std(log(HHI))	1.363	1.363	1.363	1.363
N	48,020	48,020	48,014	48,014
R^2	0.119	0.182	.	.
F	.	.	2,117	2,115

Notes: The dataset consists in the cross-section RIL and it is at the employer-year level. The table reports the OLS and TSLS regression outputs using as dependent variable the inverse hyperbolic sine transformation of the employer total investment in training. The independent variable is the log of the employment HHI, measured at a combination between an industry (NACE 3 digits) a NUTS level 2 Region, and a year. The instrumental variable consists to the log inverse number of firms across local labor markets, as described in section 4.4. "log. employees" is a control for the log. of the number of employees in each firm. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors, in parentheses. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 9: Effects on employer total investment in training: RIL panel

	OLS		IV	
	(1)	(2)	(3)	(4)
log. HHI	0.1388**	0.1382**	0.2529**	0.2631***
	(0.0584)	(0.0582)	(0.0997)	(0.0992)
log. employees		0.9833***		0.9835***
		(0.1005)		(0.1005)
Year	✓	✓	✓	✓
Employer	✓	✓	✓	✓
MDV	4.21	4.21	4.21	4.21
mean(HHI)	749.400	749.400	745.732	745.732
std(log(HHI))	1.370	1.370	1.368	1.368
N	20,686	20,686	20,676	20,676
R^2	0.705	0.708	.	.
F	.	.	5,419	5,420

Notes: The dataset consists in the panel RIL and it is at the employer-year level. The table reports the OLS and TSLS regression outputs using as dependent variables the inverse hyperbolic sine transformation of the employer total investment in training. The independent variable is the log of the employment HHI, measured at a combination between an industry (NACE 3 digits) a NUTS level 2 Region, and a year. The instrumental variable consists to the log inverse number of firms across local labor markets, as described in section 4.4. "log. employees" is a control for the log. of the number of employees in each firm. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors, in parentheses. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 10: Effects on labor productivity: training investment per worker

	OLS		IV	
	(1)	(2)	(3)	(4)
IHS. cost per worker × log. HHI	-0.0159***	-0.0160***	-0.0232***	-0.0242***
	(0.0025)	(0.0028)	(0.0047)	(0.0049)
IHS. cost per worker	0.1054***	0.1059***	0.1586***	0.1635***
	(0.0184)	(0.0210)	(0.0344)	(0.0355)
log. HHI		0.0005		0.1495***
		(0.0109)		(0.0470)
Year×Region	✓	✓	✓	✓
Year×Industry	✓	✓	✓	✓
MDV	3.81	3.81	3.81	3.81
mean(HHI)	1,819	1,819	1,819	1,819
std(log(HHI))	1.319	1.319	1.319	1.319
N	5,829	5,829	5,829	5,829
R^2	0.995	0.995	.	.
F	.	.	2,054	128

Notes: The dataset consists in the matched RIL-ORBIS dataset and it is at the local labor market level, combination between a year, NUTS level 2, and NACE 3 dig. The table reports the OLS and TSLS regression outputs using as dependent variables the log. avg. value-added per worker. The independent variable is the IHS. of the market average employer training investment per worker, the log of the employment HHI, and their interaction. The instrumental variable consists to the log inverse number of firms across local labor markets, as described in section 4.4, and the interaction with avg. IHS training cost per worker. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors, in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 11: Effects on labor productivity: market level IHS training prob.

	OLS		IV	
	(1)	(2)	(3)	(4)
IHS. training × log. HHI	-0.0560***	-0.0478***	-0.0833***	-0.0926***
	(0.0138)	(0.0180)	(0.0308)	(0.0317)
IHS. training prob.	0.3719***	0.3131**	0.5682**	0.6587***
	(0.1018)	(0.1310)	(0.2227)	(0.2293)
log. HHI		-0.0089		-0.1683
		(0.0125)		(0.1339)
Year×Region	✓	✓	✓	✓
Year×Industry	✓	✓	✓	✓
MDV	3.81	3.81	3.81	3.81
mean(HHI)	1,819	1,819	1,819	1,832
std(log(HHI))	1.319	1.319	1.319	1.321
N	5,829	5,829	5,829	5,847
R^2	0.995	0.995	.	.
F	.	.	1,342	15.5

Notes: The dataset consists in the matched RIL-ORBIS dataset and it is at the local labor market level, combination between a year, NUTS level 2, and NACE 3 dig. The table reports the OLS and TSLS regression outputs using as dependent variables the log. avg. value-added per worker. The independent variable is the market average of the probability an employer provided training, the log of the employment HHI, and their interaction. The instrumental variable consists to the log inverse number of firms across local labor markets, as described in section 4.4, and the interaction with market avg. training probability. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors, in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 12: Effects on average market yearly wages: market level IHS training prob.

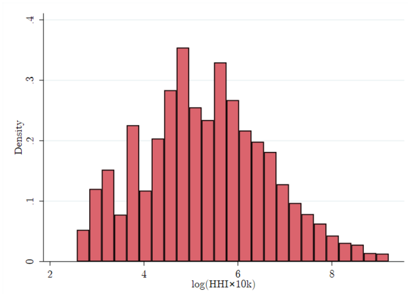
	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
log. HHI	-0.0208***	-0.0212***	-0.0211***	-0.0886***	-0.0903***	-0.0897***
	(0.0030)	(0.0030)	(0.0030)	(0.0145)	(0.0146)	(0.0146)
IHS training prob.		0.0226***			0.0283***	
		(0.0071)			(0.0076)	
IHS investment per worker			0.0028**			0.0036***
			(0.0011)			(0.0012)
Year×Region	✓	✓	✓	✓	✓	✓
Year×Industry	✓	✓	✓	✓	✓	✓
MDV	9.94	9.94	9.94	9.94	9.94	9.94
mean(HHI)	1,819	1,819	1,819	1,819	1,819	1,819
std(log(HHI))	1.319	1.319	1.319	1.319	1.319	1.319
N	5,829	5,829	5,829	5,829	5,829	5,829
R^2	0.699	0.699	0.699	.	.	.
F	.	.	.	258	256	257

Notes: The dataset consists in the matched RIL-ORBIS dataset and it is at the local labor market level, combination between a year, NUTS level 2, and NACE 3 dig. The table reports the OLS and TSLS regression outputs using as dependent variables the log. avg. yearly wages. The independent variable is the IHS market level employer investment in training per worker (IHS investment per worker) or the IHS market average of the probability an employer provided training (IHS training prob.), as well as the log of the employment HHI (log. HHI). The instrumental variable consists to the log inverse number of firms across local labor markets, as described in section 4.4, and the interaction with market avg. training probability. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors, in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

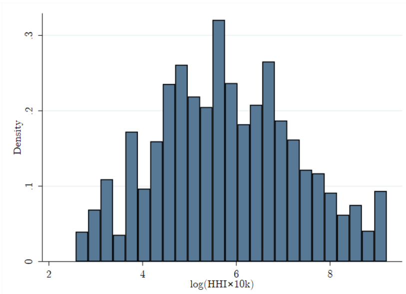
List of Figures

Figure 1: Histograms of employer HHI across employers, workers, and markets

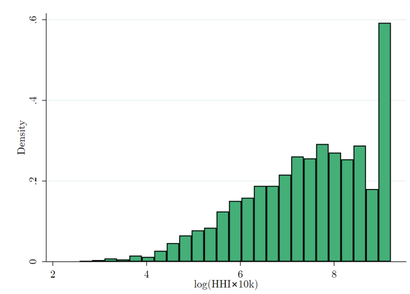
(a) Across employers



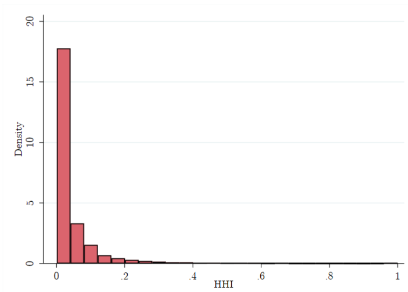
(b) Across Workers



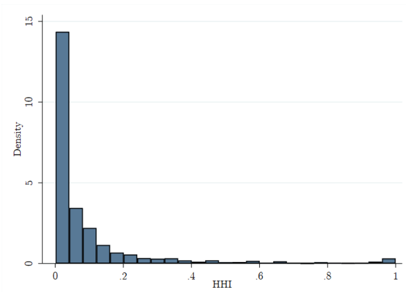
(c) Across Markets



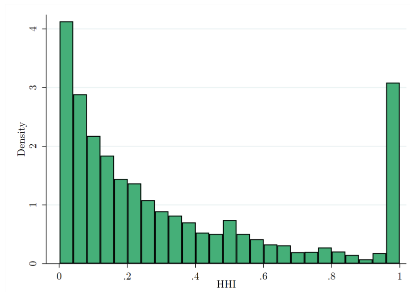
(d) Across employers



(e) Across Workers



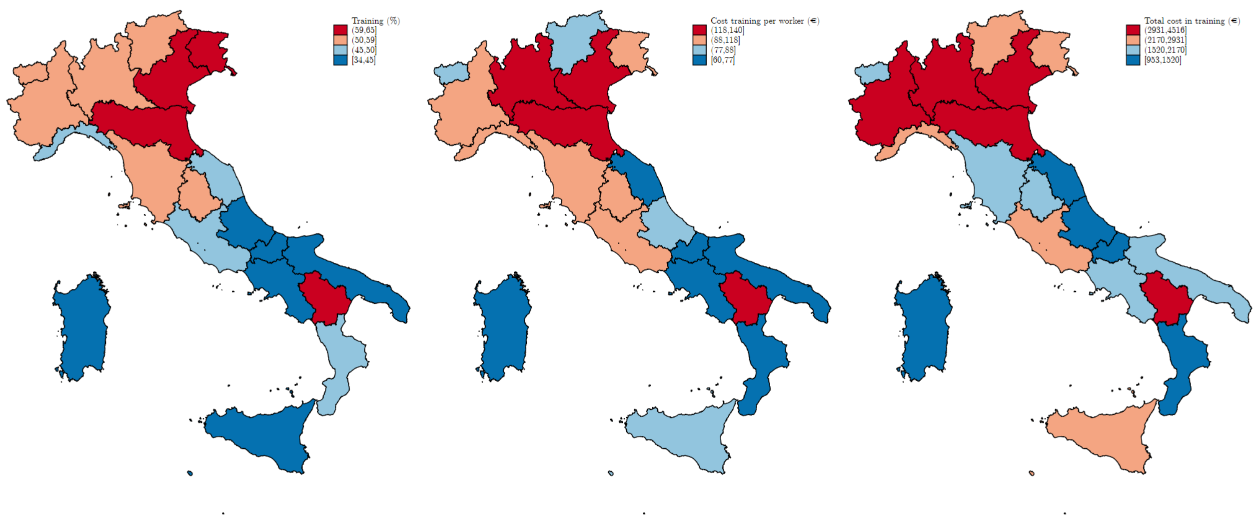
(f) Across Markets



Note: The histograms show the HHI distributions for the year 2018 across three different definitions. All the HHIs are measured at the local labor market level, considered as a combination between a NUTS level 2 region, a NACE 3 digit industry, and a year. The left (red) histograms display the HHI at the employer level, i.e., weighted for the number of employers in each local labor market. In the center (blue) the HHI distribution across workers, i.e., weighted for the number of workers in each market. In the right (green) the HHI across local labor market, i.e., whether the different local labor market are not weighted for neither the number of employer nor the number of workers. In the top panel the logarithmic transformation of the HHI multiplied by 10,000; in the bottom the level of HHI.

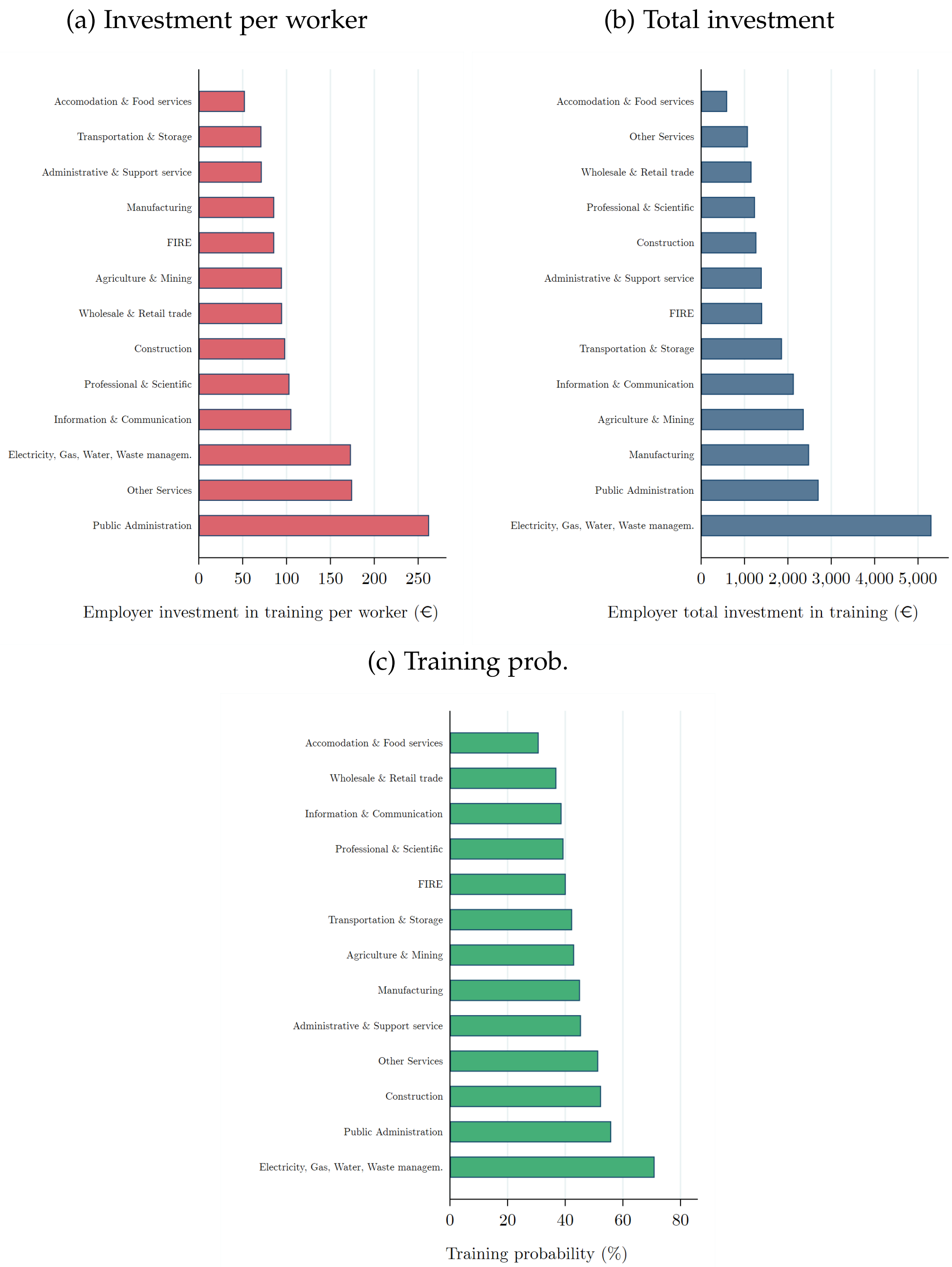
Figure 2: Maps employer training investments across NUTS level 2 region

(a) Training prob. (b) Investment per worker (c) Total investment



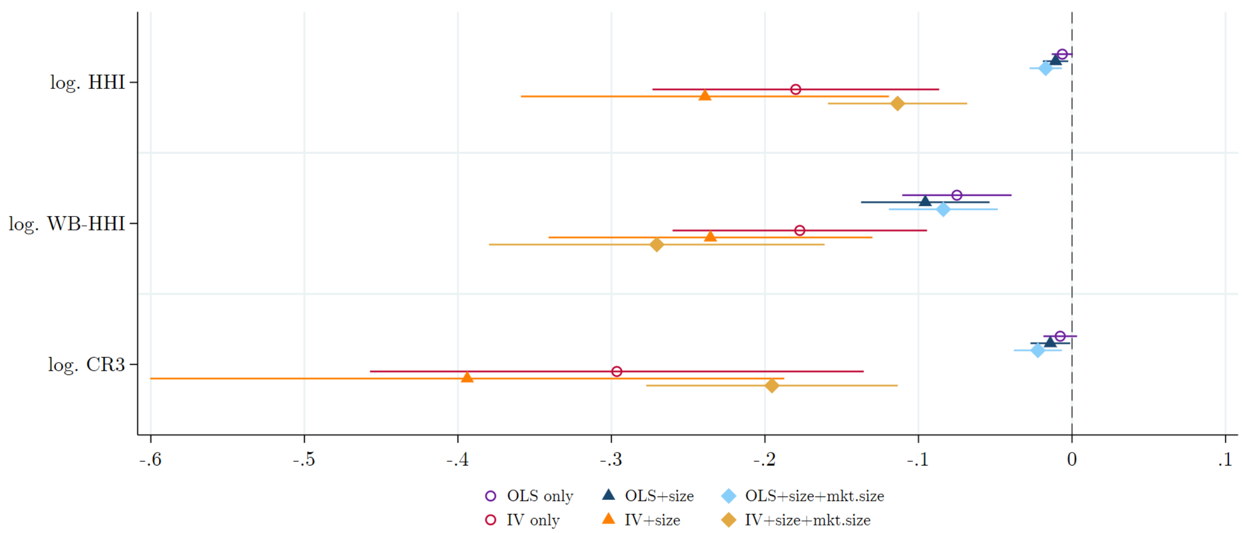
Note: Maps of training investment across NUTS level 2 region. Panel (a) illustrated the average probability that an employer provides any form of training to her workforce; Panel (b) the average yearly amount of euro investment per worker; Panel (c) the total amount invested by an employer in training. All the measures are aggregated at the NUTS level 2 region and weighted by the RIL sampling weights. Each map is split by the corresponding quartiles.

Figure 3: Employer-provided training investment across industry sectors



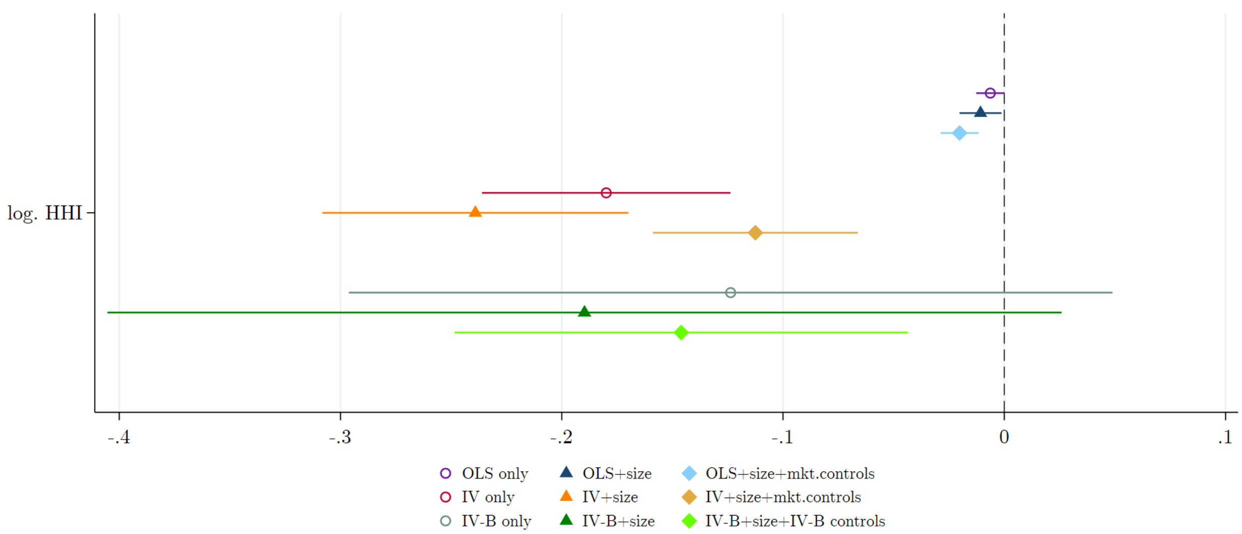
Panel (a) illustrated the average yearly amount of euro investment per worker; Panel (b) the total amount invested by an employer in training; Panel (c) the average probability that an employer provides any form of training to her workforce. All the measures are aggregated at the industry sector level and weighted by the RIL sampling weights. These industry sectors are created following NACE level 1, as follow "Agriculture & Mining" includes NACE 1 digit codes A and B; "Manufacturing"= C; "Electricity, Gas, Water, Waste manag."=(D, E); "Construnction"=F; "Wholesale & Retail Trade"=G; "Transportation & Storage"=H; "Accomodation & Food Service"=I; "Information & Communication"=J; "FIRE" = (K, L); "Professional & Scientific"=M; "Administrative & Support service"=N; "Public Administration"=(O,P,Q); "Other Services"=(R,S,T,U).

Figure 4: Wage elasticity of employer concentration: Sensitivity to concentration indexes



Note: The figure plots both the OLS and TSLS estimated wage elasticity of employer concentration and their 95% confidence intervals considering different concentration measures, and different set of controls. The ”size” control measures the number of workers employed by each employer. The ”market size” controls include the log. unemployment rate and the log. of the total number of employees in a local labor market. A local labor market is defined as a combination between a NUTS level 2 region, and NACE 3 digit industry, and a year. All the specification controls for year and employer fixed effects. The independent variables are: (i) log. HHI consider the preferred definition described as the log. employment Herfindahl-Hirshman index; (ii) WB-HHI is the log. wage-bill Herfindahl-Hirschman index, i.e., the sum of squares of wage-bill share rather than employment shares; and (iii) the log. CR3 is the log. of the employment concentration ratio of the three largest employers in a local labor market, i.e., the sum of the employment shares of these firms. Standard errors are clustered at the NUTS level 2 region level. The results of log. HHI are the same reported in Table **??**

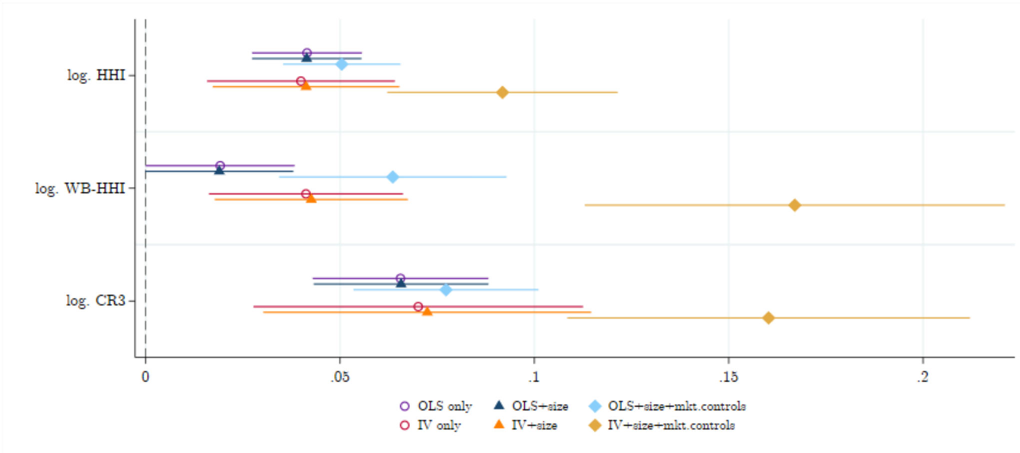
Figure 5: Wage elasticity of employer concentration: Robustness alternative IV



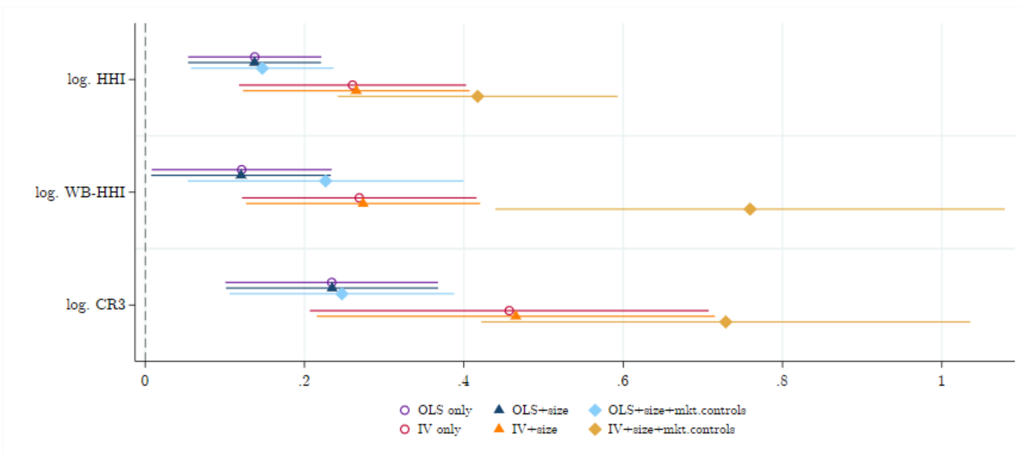
Note: The figure plots both the OLS and TSLS estimated wage elasticity of employer concentration and their 95% confidence intervals considering different the standard instrument as in Equation 25, as well as the "Bartik instrument" (IV-B) of Equation 26. The "size" control measures the number of workers employed by each employer. The "market size" controls include the log. unemployment rate and the log. of the total number of employees in a local labor market. The IV-B controls include (i) the "exposure control", (ii) actual employment growth rate, and (iii) the predicted employment growth rate; as described in Section 4.4.1. A local labor market is defined as a combination between a NUTS level 2 region, and NACE 3 digit industry, and a year. All the specification controls for year and employer fixed effects. Standard errors are clustered at the NUTS level 2 region level.

Figure 6: Effects on Employer Provided Training: Sensitivity to concentration indexes

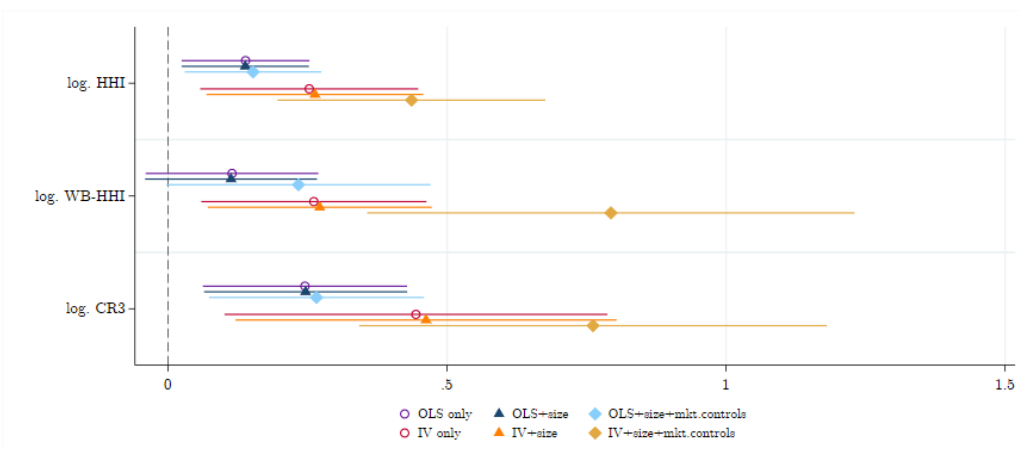
(a) Training Probability



(b) IHS Training Investment Cost per Worker



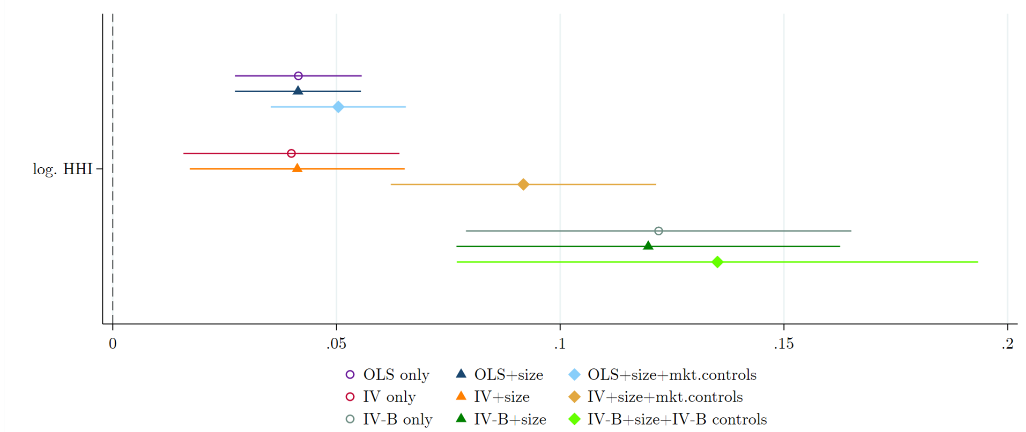
(c) IHS Total Training Investment Cost



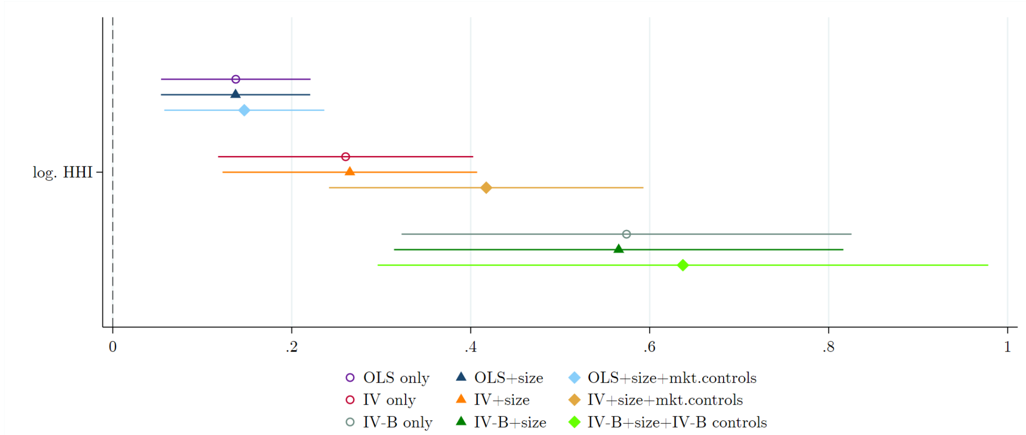
Note: The figure plots the OLS and TSLS estimated effects on (a) the probability an employer provides training, (b) the IHS of the employer investment in training per worker, and (c) the IHS employer total investment in training. The "size" control measures the number of workers employed by each employer. The "market controls" include the log. unemployment rate and the log. of the total number of employees in a local labor market. All the specification controls for year and employer fixed effects. The three concentration indexes are: (i) the log.HHI; (ii) the log. wage-bill HHI (WB-HHI), and (iii) the log. of 3-subject Concentration Ratio (CR3).

Figure 7: Effects on Employer Provided Training: Robustness alternative IV

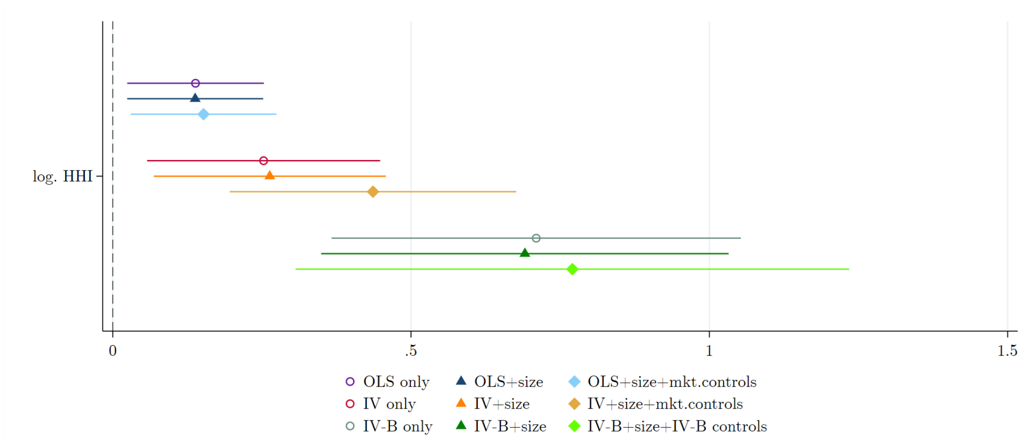
(a) Training Probability



(b) IHS Training Investment Cost per Worker



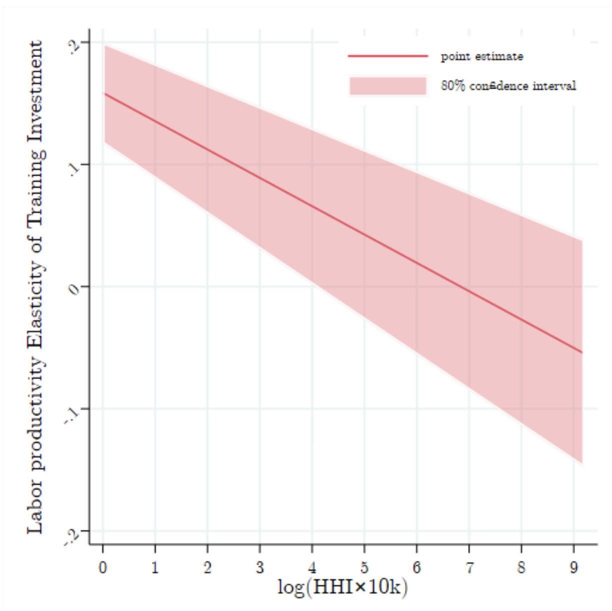
(c) IHS Total Training Investment Cost



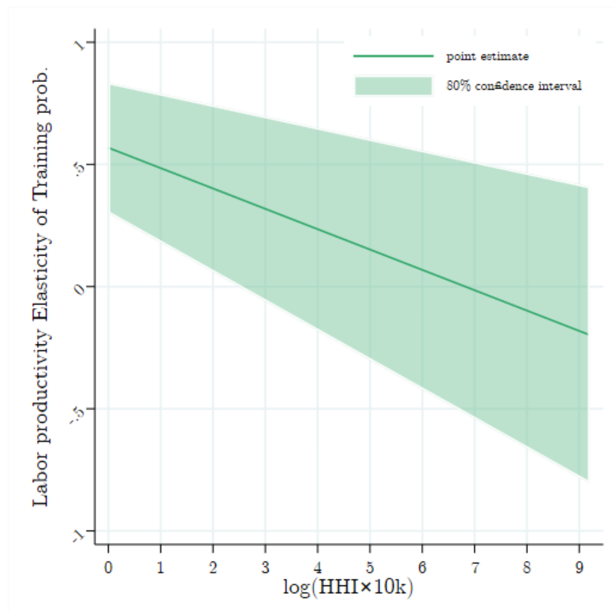
Note: The figure plots both OLS and TSLS estimated effects on (a) the probability an employer provides training, (b) the IHS of the employer investment in training per worker, and (c) the IHS employer total investment in training and their 95% confidence intervals considering different the standard instrument as in Equation 25, as well as the ”Bartik instrument” (IV-B) of Equation 26. The ”size” control measures the number of workers employed by each employer. The ”market size” controls include the log. unemployment rate and the log. of the total number of employees in a local labor market. The IV-B controls include (i) the ”exposure control”, (ii) actual employment growth rate, and (iii) the predicted employment growth rate; as described in Section 4.4.1. All the specification controls for year and employer fixed effects.

Figure 8: Labor Productivity Elasticity of Training

(a) IHS Training investment per worker



(b) IHS Training probability



Note: The figure plots the estimated labor productivity elasticity of the inverse hyperbolic sine transformation (IHS) of the market level employer provided training investment (Panel a) and training probability (Panel b). Specifically, it illustrates the results of Equation 22 using the estimates from Tables 10 and 11, Column (4).

A Extra Tables

Table T1: Effects on wages: Sensitivity to Local Labor Market definition

Dependent Variable:	avg. log. yearly wages				
	NACE 2	NACE 3	NACE 4	NACE 5	NACE 6
PANEL A: *NUTS level 2*					
log(HHI)	-0.1202***	-0.1799***	-0.2124***	-0.2300***	-0.2645***
	(0.0066)	(0.0074)	(0.0066)	(0.0064)	(0.0062)
Year	✓	✓	✓	✓	✓
Employer	✓	✓	✓	✓	✓
MDV	9.707	9.707	9.707	9.707	9.707
mean(HHI)	246.333	441.446	719.881	893.668	1008.017
std(log(HHI))	1.296	1.364	1.457	1.496	1.518
N	2,591,925	2,591,777	2,591,690	2,591,616	2,591,315
F	37,080	30,687	48,317	52,428	57,291
PANEL B: *NUTS level 3*					
log(HHI)	-0.1282***	-0.1579***	-0.1998***	-0.2262***	-0.2557***
	(0.0077)	(0.0070)	(0.0062)	(0.0061)	(0.0059)
Year	✓	✓	✓	✓	✓
Employer	✓	✓	✓	✓	✓
MDV	9.708	9.708	9.708	9.708	9.708
mean(HHI)	626.093	1071.843	1669.741	2022.294	2221.955
std(log(HHI))	1.259	1.312	1.386	1.414	1.426
N	2,584,746	2,584,666	2,584,610	2,584,533	2,584,280
F	34,217	47,320	63,458	72,737	77,276

Notes: The dataset is at the employer-year level. The table reports the TSLS regression outputs using as dependent variables the employer average yearly wages. The independent variable is the log of the employment HHI, measured at different classifications of industry (NACE 2 to 6 digit) and geographies (Panel A uses NUTS level 2 and Panel B NUTS level 3). The instrumental variable consists to the log inverse number of firms across local labor markets, as described in Equation 25. The instrument changes according to the different local labor market definitions. MDV reports the Mean of the Dependent Variable. F displays the Kleibergen-Papp Wald F statistic. Robust standard errors, in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table T2: Effects on wages: First Stages

	IV		IV-B			
	(1)	(2)	(3)	(4)	(5)	(6)
IV	0.5460***	63.3382***				
	(0.0026)	(0.2197)				
IV-B			0.0193***	0.0287***	0.4650***	0.4030***
			(0.0003)	(0.0003)	(0.0004)	(0.0004)
exposure control				2.6977***		5.0036***
				(0.0103)		(0.0073)
actual employm. growth				0.8824***		1.3155***
				(0.0019)		(0.0026)
predicted employm. growth				-1.0158***		0.2071***
				(0.0032)		(0.0082)
Year	✓		✓	✓		
Year×Region		✓			✓	✓
Year×Industry		✓			✓	✓
Employer	✓		✓	✓		
N	2,591,777	2,691,663	1,994,661	1,994,661	2,103,652	2,103,652

Notes: The table reports the first-stage regression for the HHI instrument. "IV" refers to the instrument described in Equation 25, while "IV-B" to the instrument described in Equations 26. "Exposure control", "predicted employment growth", and "actual employment growth" are the additional controls for the Bartik instrument (IV-B), as described in Section 4.4. Robust standard errors, in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table T3: Effects on training: First Stages

	Cross-section		Panel	
	(1)	(2)	(3)	(4)
IV	0.8123***	0.8124***	84.2460***	84.2171***
	(0.0110)	(0.0110)	(1.8312)	(1.8314)
log. employees		0.0125		-0.0036
		(0.0138)		(0.0035)
Year	✓	✓		
Year×Region			✓	✓
Year×Industry			✓	✓
Employer	✓	✓		
N	20,676	20,676	48,014	48,014

Notes: The table reports the first-stage regression for the HHI instrument. "IV" refers to the instrument described in Equation 25. Robust standard errors, in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table T4: Effects on training: First Stages (Bartik IV)

	Panel			Cross-section		
	(1)	(2)	(3)	(4)	(5)	(6)
IV-B	0.2223***	0.2222***	0.1728***	0.5603***	0.5604***	0.4781***
	(0.0058)	(0.0058)	(0.0054)	(0.0028)	(0.0028)	(0.0026)
log. employees		0.0245	0.0195		0.0049	0.0040
		(0.0163)	(0.0144)		(0.0027)	(0.0023)
exposure control			6.8610***			5.0018***
			(0.1489)			(0.0492)
actual employm. growth			0.4957***			1.8484***
			(0.0502)			(0.0246)
predicted employm. growth			-1.1767***			-1.6958***
			(0.0516)			(0.0506)
Year	✓	✓	✓			
Year×Region				✓	✓	✓
Year×Industry				✓	✓	✓
Employer	✓	✓	✓			
N	17,372	17,372	17,372	44,247	44,247	44,247

Notes: The table reports the first-stage regression for the HHI instrument. ”IV-B” denotes to the instrument described in Equations 26. ”Exposure control”, ”predicted employment growth”, and ”actual employment growth” are the additional controls for the Bartik instrument (IV-B), as described in Section 4.4. Robust standard errors, in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table T5: Robustness for product concentration: Wages

	OLS		IV	
	(1)	(2)	(3)	(4)
log. employment HHI	-0.0063***	-0.0172***	-0.1842***	-0.0120***
	(0.0012)	(0.0007)	(0.0076)	(0.0033)
log. product HHI	-0.0004	0.0287***	0.0053***	0.0285***
	(0.0006)	(0.0005)	(0.0007)	(0.0005)
Year	✓		✓	
Employer	✓		✓	
Year×Region		✓		✓
Year×Industry		✓		✓
MDV	9.707	9.669	9.707	9.669
mean(HHI)	441.700	440.714	441.446	440.629
std(log(HHI))	1.364	1.365	1.364	1.365
N	2,591,927	2,691,763	2,591,777	2,691,663
R^2	0.704	0.139	.	.
F	.	.	29,334	1,372

Notes: The dataset consists in the AIDA dataset and it is at the employer-year level. The table reports the OLS and TSLS regression outputs using as dependent variable the log. average wages for each employer. The independent variables are (i) the log of the employment HHI, measured at a combination between an industry (NACE 3 digits) a NUTS level 2 Region, and a year; (ii) the log of the sum of the squared revenues national share of all the firm within the same market (log product HHI). The instrumental variable of log employment HHI consists to the log inverse number of firms across local labor markets, as described in section 4.4. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table T6: Robustness for product concentration: Training probability

	OLS		IV	
	(1)	(2)	(3)	(4)
log. employment HHI	0.0333***	0.0341***	0.0261*	0.0291**
	(0.0076)	(0.0076)	(0.0140)	(0.0139)
log. product HHI	0.0137***	0.0122***	0.0149***	0.0130***
	(0.0040)	(0.0040)	(0.0045)	(0.0045)
log. employees		0.1256***		0.1255***
		(0.0124)		(0.0124)
Year	✓	✓	✓	✓
Employer	✓	✓	✓	✓
MDV	.624	.624	.624	.624
mean(HHI)	749.400	749.400	745.732	745.732
std(log(HHI))	1.370	1.370	1.368	1.368
N	20,686	20,686	20,676	20,676
R^2	0.722	0.724	.	.
F	.	.	4,362	4,360

Notes: The dataset consists in the panel RIL and it is at the employer-year level. The table reports the OLS and TSLS regression outputs using as dependent variable the training dummy, which is equal to 1 if the employer has invested in training. The independent variables are (i) the log of the employment HHI, measured at a combination between an industry (NACE 3 digits) a NUTS level 2 Region, and a year; (ii) the log of the sum of the squared revenues national share of all the firm within the same market (log product HHI). The instrumental variable of log employment HHI consists to the log inverse number of firms across local labor markets, as described in section 4.4. "log. employees" is a control for the log. of the number of employees in each firm. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors, in parentheses. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table T7: Robustness for product concentration: IHS training investment per worker

	OLS		IV	
	(1)	(2)	(3)	(4)
log. employment HHI	0.1104**	0.1133**	0.2386***	0.2496***
	(0.0449)	(0.0449)	(0.0826)	(0.0824)
log. product HHI	0.0453*	0.0400*	0.0233	0.0165
	(0.0238)	(0.0238)	(0.0266)	(0.0266)
log. employees		0.4465***		0.4492***
		(0.0735)		(0.0736)
Year	✓	✓	✓	✓
Employer	✓	✓	✓	✓
MDV	2.61	2.61	2.61	2.61
mean(HHI)	749.400	749.400	745.732	745.732
std(log(HHI))	1.370	1.370	1.368	1.368
N	20,686	20,686	20,676	20,676
R^2	0.694	0.695	.	.
F	.	.	4,362	4,360

Notes: The dataset consists in the panel RIL and it is at the employer-year level. The table reports the OLS and TSLS regression outputs using as dependent variable the inverse hyperbolic sine transformation of the employer total investment in training. The independent variables are (i) the log of the employment HHI, measured at a combination between an industry (NACE 3 digits) a NUTS level 2 Region, and a year; (ii) the log of the sum of the squared revenues national share of all the firm within the same market (log product HHI). The instrumental variable of log employment HHI consists to the log inverse number of firms across local labor markets, as described in section 4.4. "log. employees" is a control for the log. of the number of employees in each firm. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors, in parentheses. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table T8: Robustness for product concentration: IHS total training investment

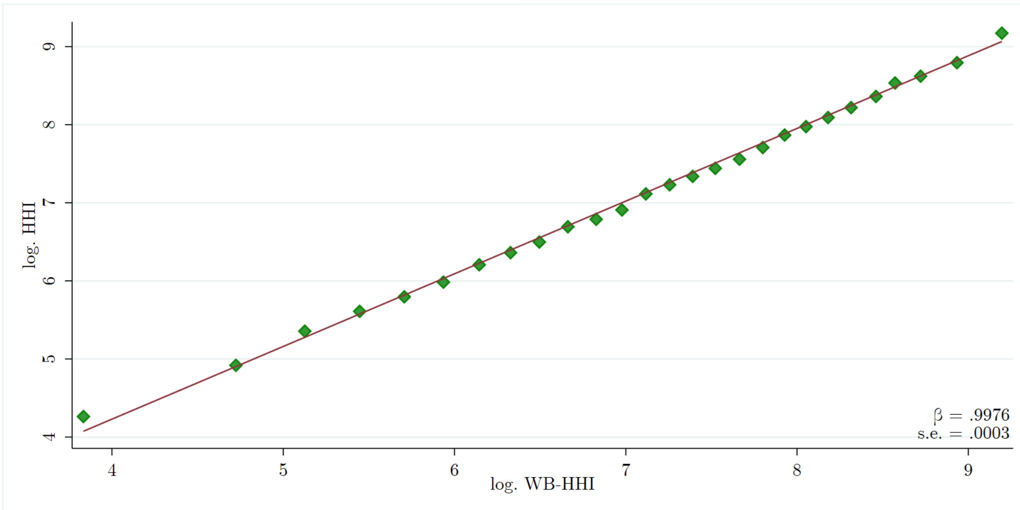
	OLS		IV	
	(1)	(2)	(3)	(4)
log. employment HHI	0.1098*	0.1162*	0.2266**	0.2507**
	(0.0616)	(0.0613)	(0.1132)	(0.1127)
log. product HHI	0.0483	0.0367	0.0282	0.0134
	(0.0327)	(0.0326)	(0.0364)	(0.0363)
log. employees		0.9792***		0.9819***
		(0.1005)		(0.1006)
Year	✓	✓	✓	✓
Employer	✓	✓	✓	✓
MDV	4.21	4.21	4.21	4.21
mean(HHI)	749.400	749.400	745.732	745.732
std(log(HHI))	1.370	1.370	1.368	1.368
N	20,686	20,686	20,676	20,676
R^2	0.705	0.708	.	.
F	.	.	4,362	4,360

Notes: The dataset consists in the panel RIL and it is at the employer-year level. The table reports the OLS and TSLS regression outputs using as dependent variables the training dummy, which is equal to 1 if the employer has invested in training. The independent variables are (i) the log of the employment HHI, measured at a combination between an industry (NACE 3 digits) a NUTS level 2 Region, and a year; (ii) the log of the sum of the squared revenues national share of all the firm within the same market (log product HHI). The instrumental variable of log employment HHI consists to the log inverse number of firms across local labor markets, as described in section 4.4. "log. employees" is a control for the log. of the number of employees in each firm. MDV reports the Mean of the Dependent Variable. F reports the Kleibergen-Paap Wald F statistic from the regression. Robust standard errors, in parentheses. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

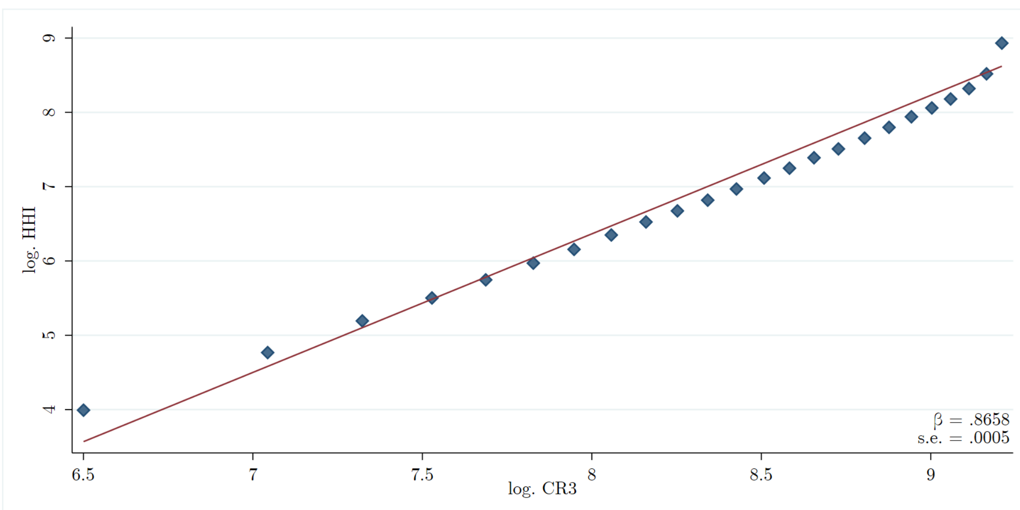
B Extra Figures

Figure F8: Correlation between different concentration measures

(a) Wage-bill HHI



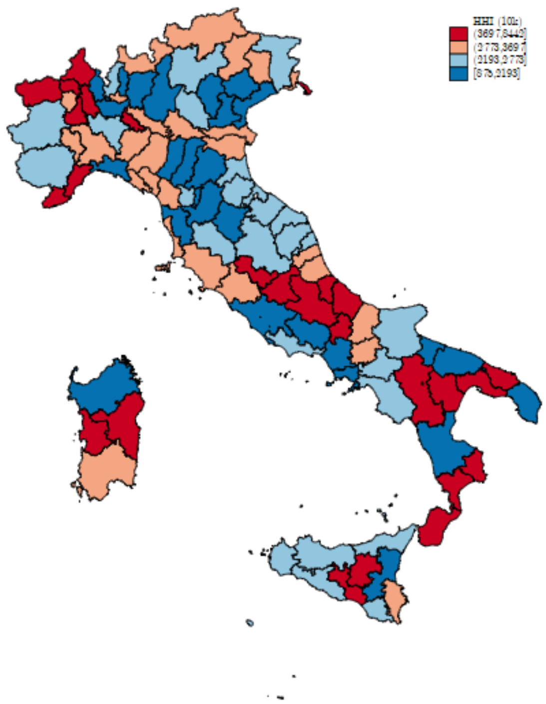
(b) 3-Subject Concentration Ratio



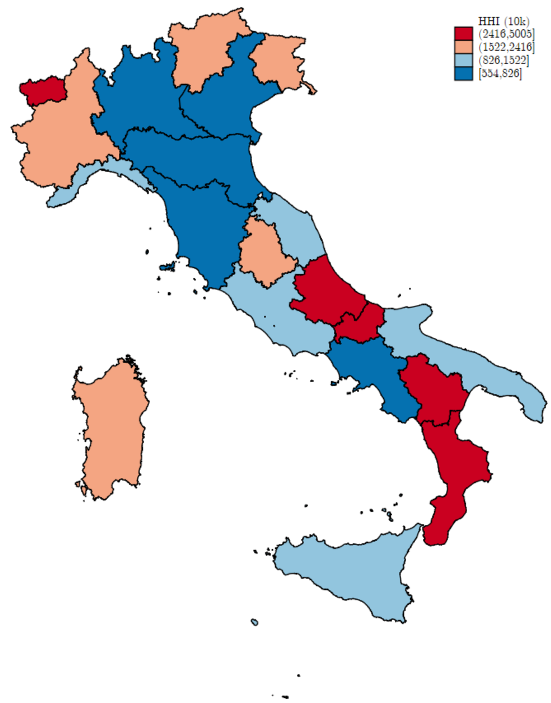
Note: Binned scatter plots between the employemnt HHI (HHI), wage-bill HHI (WB-HHI), and the employement 3-Subject concentration ratio (CR3); as described in Section 3.1.1. An observation is a combination between a year, NACE 3 digit industry, and NUTS level 2 region.

Figure F8: Employer concentration across different local labor market definitions

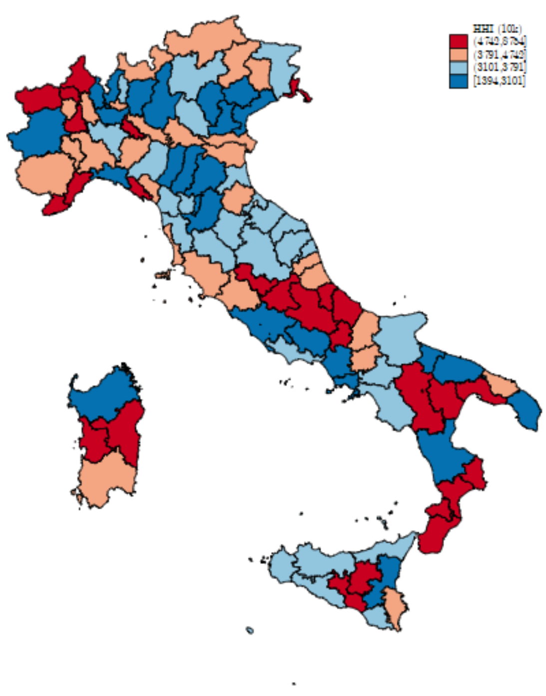
(a) LLM = NUTS 3 × NACE 3



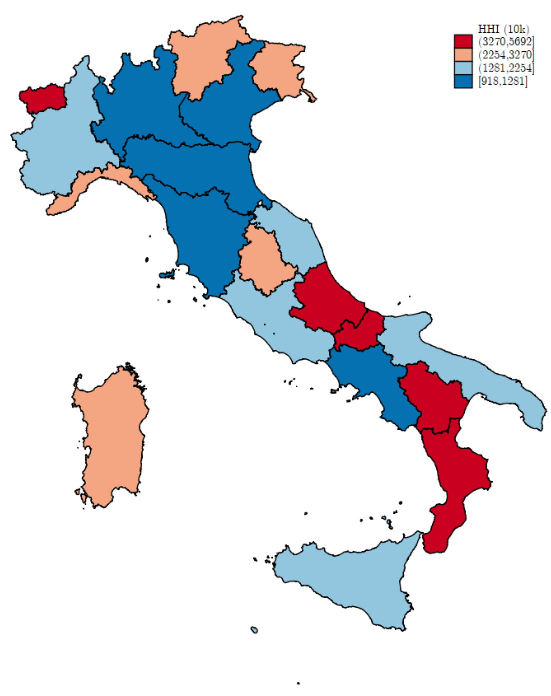
(b) LLM = NUTS 2 × NACE 3



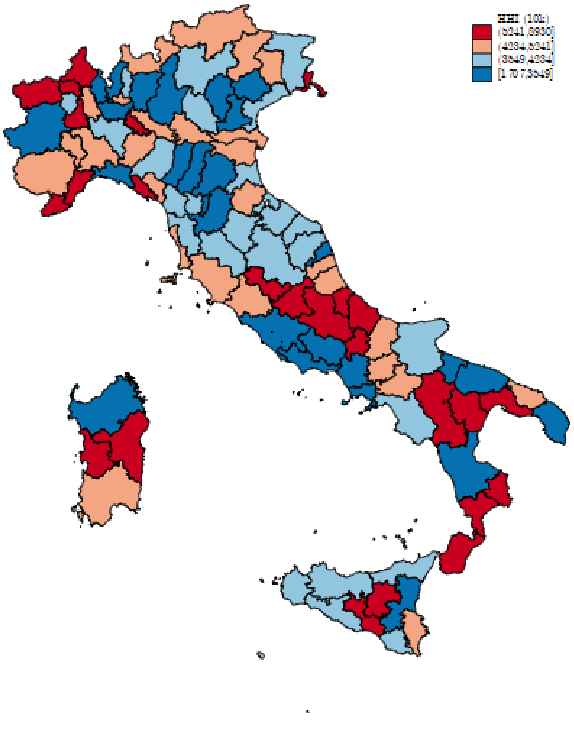
(c) LLM = NUTS 3 × NACE 4



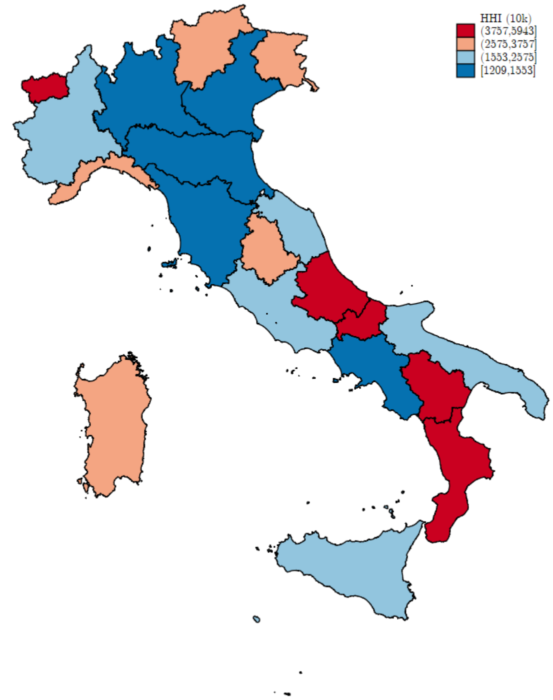
(d) LLM = NUTS 2 × NACE 4



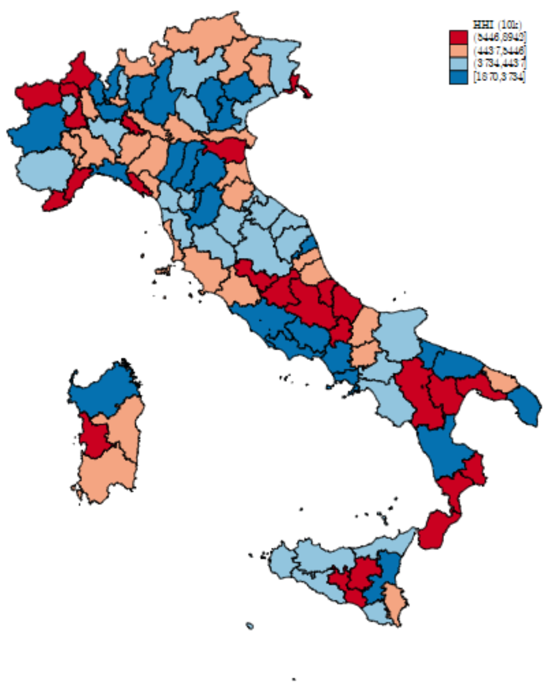
(e) LLM = NUTS 3 × NACE 5



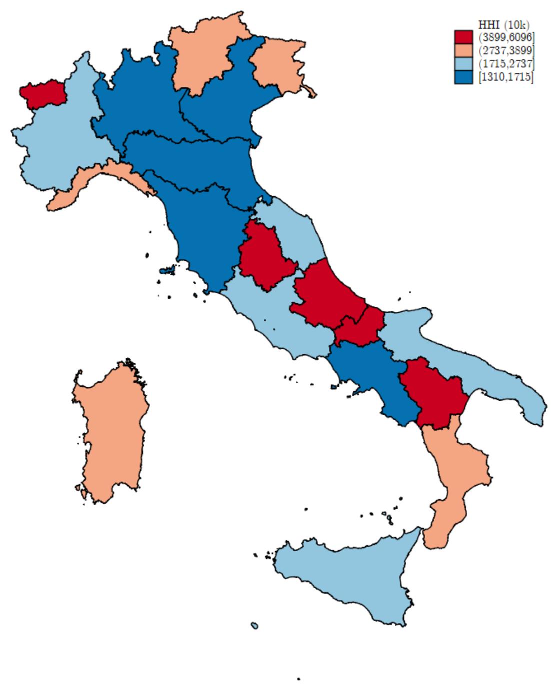
(f) LLM = NUTS 2 × NACE 5



(g) LLM = NUTS 3 × NACE 6



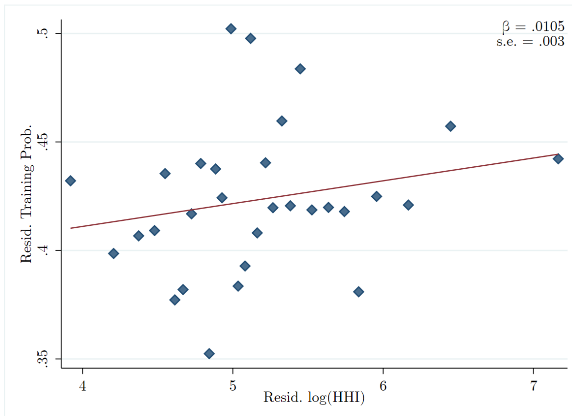
(h) LLM = NUTS 2 × NACE 6



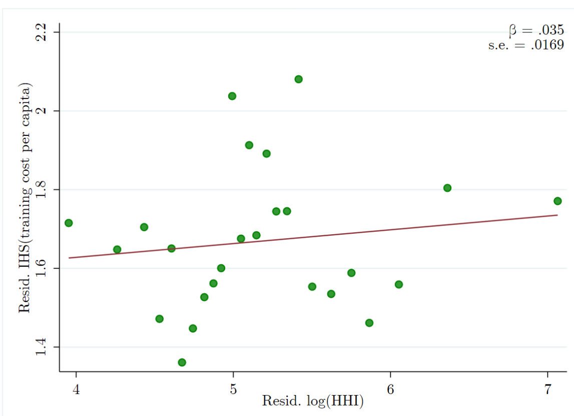
Note: Maps of employer concentration (HHI) across different definition of a local labor market for the year 2018. A local labor market (LLM) is defined as a combination between a NUTS area and a NACE industry. On the right, I use the NUTS level 3 provinces, on the left the NUTS level 2 regions. From top to bottom, I use the NACE 3digit, 4 digit, 5 digit, and 6 digit. All the measures are aggregated at the NUTS corresponding area, weighted by the number of employees in each corresponding NACE industry. Each map is split by the corresponding quartiles.

Figure F8: Binned scatter plot of log. HHI on Training measures

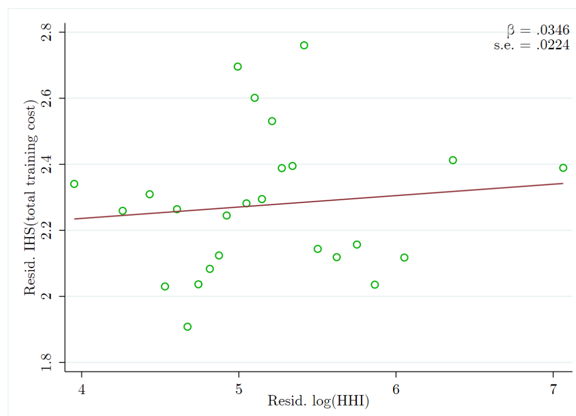
(a) Training Prob.



(b) IHS. training cost per worker



(c) IHS. total training cost



Note: Binned scatter plots of (a) probability that an employer provides training, (b) the inverse hyperbolic sine transformation IHS) of the amount of euro invested in the training per worker by an employer (c) the IHS of the total amount of euro invested over the log. HHI. The binned scatter plots are computed after residualizing both variables for the log. of the number of each employees, and the year × NACE 3 digit industry and year × NUTS 2 level fixed effects. Both plots and regressions are also computed considering the RIL weights. Each observation is an employer from the RIL cross-section sample. β and *s.e* report respectively the beta-coefficient and its standard error from the regressions between each residualized outcome variable and the residualized independent variable (log.HHI).

C Conceptual Framework: Mathematical derivations

To derive the labor supply of Equation 1, I adopted a three steps process: in the first stage, the representative household decides how much to consume. In the other two stages, instead, she minimizes the labor disutility with respect to the desired amount of consumption. In the first step:

$$\max_{\{\mathbf{C},\mathbf{N}\}} U\left(\mathbf{C} - \frac{1+\varphi}{\varphi}\mathbf{N}^{\frac{1+\varphi}{\varphi}}\right)$$
$$\text{s.t} \quad \mathbf{C} = \mathbf{N}\mathbf{W}$$

Taking the first order necessary conditions with respect to **C** and **N** leads to

$$\begin{cases} U' = \lambda \\ U'\mathbf{N}^{\frac{1}{\varphi}} = \lambda \mathbf{W} \end{cases}$$

Reaching the "solution" to the first stage problem:

$$\mathbf{N}^{\frac{1}{\varphi}} = \mathbf{W} \tag{27}$$

The problem at the second stage reads as

$$\mathbf{N} := \min_{\overline{N}_j} \left\{ \int_0^1 \overline{N}_j^{\frac{\theta+1}{\theta}} \, \mathrm{d}j \right\}^{\frac{\theta}{\theta+1}} \tag{28}$$

s.t.

$$\int_0^1 W_j N_j \, \mathrm{d}j \geq \mathbf{C} \tag{29}$$

$$\overline{N}_j := N_j G(T)^{-1} \tag{30}$$

For the sake of clarity, I define with the "bar" those indexes that includes the disutility effects of the training components. Without bar if they ignore the training component. Then, I define the wages index **W** such that $\mathbf{WN} = \int_0^1 W_j N_j \, dj$; and $\overline{W}_j$, such that $\int_0^1 W_j N_j dj = \int_0^1 \overline{W}_j \overline{N}_j dj$.

Taking the first order condition brings to the following

$$\left[\int_0^1 \overline{N}_j^{\frac{\theta+1}{\theta}} dj\right]^{-\frac{1}{\theta+1}} \overline{N}_j^{\frac{1}{\theta}} = \lambda \overline{W}_j \tag{31}$$

By multiplying both sides for $\overline{N}_j$ and integrating over j, and using the following equalities $\left[\int \overline{N}_j^{\frac{\theta+1}{\theta}} dj\right]^{-\frac{1}{\theta+1}} = \mathbf{N}^{-\frac{1}{\theta}}$ and $\int \overline{N}_j^{\frac{\theta+1}{\theta}} dj = \mathbf{N}^{\frac{\theta+1}{\theta}}$,

$$\mathbf{N}^{\frac{\theta+1}{\theta}-\frac{1}{\theta}} \int_0^1 \overline{N}_j^{\frac{1}{\theta}} dj = \lambda \int_0^1 \overline{W}_j \overline{N}_j \tag{32}$$

Using the definition of $\mathbf{W}$

$$\mathbf{W}^{-1} = \lambda \tag{33}$$

Substituting 33 into 31,

$$\overline{N}_j = \left(\frac{\overline{W}_j}{\mathbf{W}}\right)^{\theta} \mathbf{N} \tag{34}$$

To derive the function of the wage index $\mathbf{W}$, multiply by $\overline{W}_j$ both side of Equation 34 and integrate

$$\int_0^1 \overline{W}_j \overline{N}_j = \mathbf{W}^{-\theta} \mathbf{N} \int_0^1 \overline{W}_j^{1+\theta} dj \tag{35}$$

$$\mathbf{W} = \left[\int_0^1 \overline{W}_j^{1+\theta} dj\right]^{\frac{1}{1+\theta}} \tag{36}$$

Finally, the problem at the third stage is

$$\overline{N}_j := \min_{\overline{n}_{ij}} \left[\sum_i \overline{n}_{ij}^{\frac{\eta+1}{\eta}}\right]^{\frac{\eta}{\eta+1}} G(T)^{-1}$$

s.t.

$$\sum_i w_{ij} n_{ij} \geq C_j$$
$$\overline{n}_{ij} := n_{ij} g(t)$$

Where as for the second stage: $\sum_i \overline{w}_{ij} \overline{n}_{ij} = \sum_i w_{ij} n_{ij}$. The first order condition is as follow

$$G(T)^{-1} \left[\sum_i \overline{n}_{ij}^{\frac{\eta+1}{\eta}} \right]^{-\frac{1}{1+\eta}} \overline{n}_{ij}^{\frac{1}{\eta}} = \lambda \overline{w}_{ij} \tag{37}$$

Through the same procedure as before of multiplying both side by $\overline{n}_{ij}$ and summing over

$$\overline{N}_j = \lambda \overline{W}_j \overline{N}_j \tag{38}$$

Substituting 37 into 38, and re-arranging

$$\overline{n}_{ij} = \left(\frac{\overline{w}_{ij}}{\overline{\overline{W}}_j} \right)^{\eta} \overline{N}_j \, G(T)^{\eta+1} \tag{39}$$

As before, we can derive $\overline{W}_j$, by multiplying 39 with $\overline{w}_{ij}$ and sum over i

$$\overline{W}_j = \left[\sum_i \overline{w}_{ij}^{1+\eta} \right]^{\frac{1}{1+\eta}} G(T) \tag{40}$$

To conclude, by combining Equations 27, 34, 39:

$$\overline{n}_{ij} = \left(\frac{\overline{w}_{ij}}{\overline{\overline{W}}_j} \right)^{\eta} \left(\frac{\overline{W}_j}{\mathbf{W}} \right)^{\theta} \mathbf{W}^{\varphi} G(T)^{\eta+1} \tag{41}$$

which is equivalent to

$$n_{ij} = \left(\frac{w_{ij}}{W_j} \right)^{\eta} \left(\frac{W_j}{\mathbf{W}} \right)^{\theta} \mathbf{W}^{\varphi} G(T)^{1+\theta} g(t)^{-1-\eta} \tag{42}$$

To obtain the inverse labor supply (as in Equation 1), invert the Equations 27, 34, 39; to express wages as function of labor and then combined.

D Deriving the elasticity of IHS-logarithmic specifications

As an extension of Bellemare and Wichman (2020), I derive the elsticity for a Inverse hyperbolic sine transformation (IHS or arcsinh) - log specification.

The hyperbolic sine transformation IHS(X) has the following form:

$$\tilde{x} = IHS(X) = log(x + \sqrt{x^2 + 1})$$

As derived by Bellemare and Wichman (2020), a useful preliminary result is that

$$\frac{\partial \tilde{x}}{\partial x} = \frac{1}{\sqrt{x^2 + 1}}$$

Therefore, considering a IHS-logarithmic specification

$$\tilde{y} = \alpha + \beta log(x) + \epsilon \tag{43}$$

$$\hat{\beta} = \frac{\partial \tilde{y}}{\partial log(x)} = \frac{\partial \tilde{y}}{\partial y}\frac{\partial y}{\partial x}\frac{\partial x}{\partial log(x)}$$

which leads to the following form for the elasticity

$$\varepsilon_{yx} := \frac{\partial y}{\partial x}\frac{x}{y} = \hat{\beta}\frac{\sqrt{y^2 + 1}}{y}$$

It can be seen that $\frac{\sqrt{y^2+1}}{y} \to 1$ very fast. Indeed, considering Equation 43 and a mean value of y of 123 (that is the mean employer provided investment in training per worker, see Table 2), the actual estimated elasticity is 1.00003 the naive elasticity estimated assuming naively a log-log specification.

Analogously, it can be showed that the elasticity of a logarithmic-IHS specification reads as follow:

$$\varepsilon = \hat{\beta}\frac{x}{\sqrt{x^2 + 1}} \to \hat{\beta}$$