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

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[work in progress]

Abstract

This paper studies the effect of employer concentration on the provision of on-the-job training and the interlink that this effect has on wages. I develop an oligopsony model of the labor market, where employers strategically decide wages and on-the-job training investment according to the level of employment concentration they face in a local labor market. High levels of employer concentration reduce both the separation and recruitment wage elasticities. Employers in highly concentrated markets find it more challenging to hire new workers and lose employees poached by competitors. On top of increasing workers' productivity, on-the-job training has an ambiguous effect on separation and recruitment wage elasticities. A set of testable predictions for training and wages are derived and confronted with comparable microdata on training in the USA and Italy. Specifically, I estimated with an instrumental variable approach that high employer concentration in a local labor market (i) positively affects the firms' training investment, (ii) reduces wages, (iii) decreases training-induced wage premium, and (iv) increases workers productivity. These findings suggest that using employer concentration as a direct measure of labor market competition underestimates the negative effect of concentration on wages.

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

JEL Codes: J24, J23, J21, J42, E24, R12

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1 Introduction

There is growing evidence on how local labor markets are highly concentrated, that is the employment in industry and geographic area is concentrated in few firms. Yet, the literature has found a surprisingly small effect of concentration on wages. This finding suggests that other mechanisms balance what the theoretical literature expects to be a clear negative effect.[1] The first contribution of this paper is to show that employer concentration spurred employers in investing in training. Two elements drive the latter. First, employers with a dominant position in a labor market extract a larger surplus from the workers' productivity; thus, they are incentivized to invest in the workers' productivity. Second, dominant firms have difficulties hiring new workers as they already employ a large share of the employees in a local labor market. Thus, by providing the required skills for the job through training, these firms can attract workers from other sectors without drastically increase the wages and given the dominant position in the market without the threat of losing their employees to competitors. The second contribution is to model the apparent contradicting results of training on the attracting/retaining and separation rate. According to the theory, it is unclear if workers are more likely to be poached after training.[2] On the one hand, it is entirely plausible for trained workers to have better outside options, consequently increasing the poaching threat and the separation rate for the employer. On the other hand, workers with many skills might see a reduction in the number of firms interested in that skill bundle, thus reducing their outside options; in this case, training can reduce the poaching threats and increase the retaining rate. Additionally, training can improve also job satisfaction increasing the retaining rate. The empirical literature confirmed this ambiguous training effect on retaining and separation rates, finding results going in both directions.[3] The third contribution provides a mechanism for the surprisingly small effect of employer concentration on wages, partially explaining the difference in estimates obtained by reduced form studies of employment concentration on wages and studies adopting a production function approach.[4] By increasing the training investment, workers located in more concentrated markets are more productive, thus ignoring this aspect leads to underestimating

[1] This result is robust to different measures of concentration and local labor market (Lipsius, 2018; Azar et al., 2020b; Schubert et al., 2020; Marinescu et al., 2021). See section 2, where I describe this literature in more detail. On monopsony power (Robinson, 1969; Boal and Ransom, 1997; Manning, 2003, 2011).

[2] See for example, Stevens (1994), Acemoglu and Pischke (1999), Manning (2003), Leuven (2005).

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

[4] For papers using a production function approach to estimate the wage markdown see Hershbein et al. (2020); Brooks et al. (2021). For a literature review on the two methods and a meta-analysis on the results, see Sokolova and Sorensen (2021).

the effect of employer concentration on wages.

Although the traditional literature on human capital has generally focused on education, the accumulation of human capital does not end with schools. In light of the ageing population and the rapidity of technological changes, training, at every stage of life, has become even more crucial. According to the EU Council (2019), promoting lifelong training is a key challenge, as they argue that "as soon as 2022, 54% of all employees will require significant upskilling and reskilling".[5] Therefore, it is important to explore the determinants that stimulate on-the-job training and how labor market concentration could affect them. Especially in the aftermath of the Covid-19 pandemic, which will cause 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). This new displacements will further aggravate the need for a deeper understanding on the mechanisms behind on-the-job training to improve the efficiency of government training and job assistance programs, such as the Trade Adjustment Assistance, which they generally obtained limited success especially during economic downturns (Hyman, 2018; Hyman and Ni, 2020).

The rationale behind the relationship between employer concentration and on-the-job training is competition between firms, whose concentration is a widely applied indicator in industrial organization and competition law. The main mechanisms for which firm competition affects training are through wages and job alternatives. Because for training to be profitable, a firm should profit more from a trained worker than an untrained one and the trained worker should not leave the training firm once she is trained. Under perfect competition, the labor market concentration does not matter, because firms are price-taker and the wages are equal to the workers' marginal productivity, independently of the level of concentration. However, by introducing market imperfections, the concentration plays an important role. For example, consistent with the standard oligopsony theory, high concentration could reduce wages if firms decide how many people to employ knowing how their employment decision will affect wage and knowing other firms' desired hiring. Additionally, if workers have imperfect information on the job alternatives or have heterogeneous preference for the workplace, a high concentration reduces the workers' suitable alternatives and in turn their bargaining power. In this setting, firms do not have to pay the workers their marginal productivity in order to prevent them to move away. Despite

[5] See also World Economic Forum (2018), The EU council document is available at:
https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1567152732425&uri=CELEX:52019XG0605(01)#ntr3-C_2019189EN.01002301-E0003

this clear-cut relation between concentration and wage, the relation between the extent of concentration and the firm sponsored training is still unsettled and difficult to predict.

Section 2 reviews the relevant literature. Section 3 introduces the model. Section 4 describes the data, Section 5 outlines the estimation procedure. Section 6 presents and discusses the results. Section 8 concludes.

2 Related Literature

This paper is related to three different literature strands and contributes to each as I explain below.

First, I contribute to the flourishing empirical literature that analyzes the effect of employer concentration on wages by extending the analysis on the effect on firm-sponsored training. Among the most recent and notable empirical contributions (Martins, 2018; Abel et al., 2018; Rinz, 2018; Lipsius, 2018; Qiu and Sojourner, 2019; Azar et al., 2019; Benmelech et al., 2020; Azar et al., 2020a,b; Arnold, 2020; Schubert et al., 2020; Marinescu et al., 2021), who found a significant but small negative effect of concentration on wages. In line with this result, Berger et al. (2019) design a structural model where firms compete à la Cournot for workers in the local labor market. They show how labor market concentration negatively affects wage and employment.[6] Overall this literature focuses on the direct relationship between concentration and wages, this paper extends it by exploring another channel through which labor market concentration could affect labor macro trends. In particular, I estimate the effect of labor market concentration on firm-sponsored training decisions. By raising worker productivity, this induced increase in training produces an indirect positive effect on wages, which may therefore explain the small negative effect observed of concentration on wages.

Second, this paper is also related to the theoretical literature that investigates the mechanisms and conditions that stimulate firm-sponsored training. My contribution is to provide empirical evidence to the mixed theoretical predictions. In a pioneering paper, Becker (1964) distinguishes human capital between general and specific. While the former has

[6] Other structural analyses that connect employer concentration to wage markdown are Jarosch et al. (2019) and Azkarate-Askasua and Zerecero (2020).

value for all the firms, the latter has value only for the incumbent firm. In this framework and under perfect competition there is no under- or over- investment in human capital. Because the workers pay for acquiring general skills, whereas the employers bear the cost of the specific ones. However, in practice, perfect competition is an unreasonable assumption and training is neither perfectly general or perfectly specific. This leads to the emergence of ambiguities. The main requirements for firms to profitably bear the cost of training are that firms can extract some rent from the marginal productivity of the workers and that the workers do not immediately leave the training firm once they are trained. Non-competitive theories of training propose different sources of labor market imperfection that enable these conditions. For example, Acemoglu and Pischke (1998) argue that if a firm has information on its workers' ability, while the outside firms do not; the incumbent firm can offer wage that are lower than the worker's productivity.[7] According to them, a rise in labor market concentration reduces the separation rate of the employees, thus it increases the expected return of training and in turn the training provision. However, this result relies on the assumptions that training is general and observable, as well as that there are no difference between the separation rate and the mark-down on wage of trained and untrained workers. Stevens (1994) proposes a new definition of "transferable training", where training has some value to at least one firm in addition to the training firm. Therefore, depending on the degree of transferability of a particular training, a rise in competition could either increase or decrease the amount of firm-sponsored training. Similarly, Lazear (2009) considers human capital with an atomized approach. According to him, human capital is the collection of different competences and each firms desires a unique mix of these competencies. This creates a wedge for investing in human capital, because the more competences a worker has the more difficult is for her to find a suitable job alternative. Thus, training increases the retention rate of the employees and can stimulate the employers to invest in human capital.[8] As such, a firm in a low concentrated area could increase training in order to reduce recruiting and other turnover costs. Given these ambiguous predictions, this paper provides empirical evidence on whether and to what extent labor market concentration affects firm-sponsored training.

Third, this paper is related to the empirical literature that links agglomeration with training

[7]Other theoretical sources of imperfect competition are credit constraints, mobility costs, search friction, heterogeneous preference over the workplace, collusion between employers. Obviously, the question of why firms do training is not new, the first analyzes can be traced back to Pigou (1912). To a detailed survey of the less recent theoretical studies, see Leuven (2005). See Manning (2003) for more general models with non-perfect competition in the labor market.

[8]Munasinghe and O'Flaherty (2005) provide evidence that indeed training reduces turnover.

provision. Mostly of this literature focuses on European countries and apprenticeships.[9] In particular, Harhoff and Kane (1997) and Muehlemann and Wolter (2011) document how the greater the number of firms in a regional area the lower is the demand of apprenticeships in Germany and Switzerland respectively. Brunello and Gambarotto (2007) show that in areas with few workers the provision of on-the-job training is less frequent. The rationale behind those results is that firms in denser areas face higher competition in the labor market, which in turn implies higher risk of poaching.[10] As aforementioned, these studies rely on agglomeration measures, which are not able to separate urban areas effects from pure labor market competition. I contribute to this literature along several dimensions. First, I focus on on-the-job training rather than apprenticeship. Apprenticeship is a particular type of vocational training which it is closer to education than training, because it is strictly regulated with certification and rigorous curricula, moreover it is limited to young people, while, due to an ageing population and technology changes, training is also crucial for older people. Second, I adopt a measure of concentration rather than agglomeration, which better gauge the competition level in a local market. Agglomeration fails to take into account the size of the firms, considering only their number. This leads to neglect the effect that firm size could have on firms' training decision, ignoring as well that higher density is correlated with more urban areas, which in turn mixes the competition effect with other possible contributing factors, such as better schools, better infrastructures, urban wage premium. Lastly, this paper explores how the relationship between labor market concentration and on-the-job training changes with the wage-setting and the retaining/separation rates. Understanding if training investment is also driven by labor supply rationale is critical to guide government training and job assistance programs. Moreover, it can help understand why training programs sometimes have limited results in improving workers' productivity.[11]

[9] Notable exceptions are Rzepka and Tamm (2016) and Méndez (2019). Yet, these paper differ from this study both in methodology and in the data used.

[10] However, Jansen et al. (2015) and Mohrenweiser et al. (2019) observe that firms do not reduce the quantity of apprenticeship after poaching events or threats, but they modify the content, mostly reducing their costs or increasing the work of the apprentices.

[11] See for example Card et al. (2010); Hyman (2018); Brunello and Wruuck (2020).

3 Model

Following Berger et al. (2019), I consider an economy consisting of a representative household with a "nested-CES utility function" and a continuum of firms. Firms are heterogeneous in two dimensions: (i) they have different exogeneous productivity z_{ij}, (ii) they inhabit a continuum of different local labor markets (from now on, I define it just as market) indexed by $j \in [0,1]$, each market has a different and exogeneously determined number of firms (M_j).

3.1 Baseline Framework

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. The representative household chooses the amount of labor to supply to each firm (n_{ij}).

The representative household problem is

$$\max_{\{n_{ij}\}} \quad u\left(\mathbf{C} - \frac{\overline{\mathbf{N}}^{1+\frac{1}{\psi}}}{1+\frac{1}{\psi}}\right)$$

$$\text{s.t.} \quad \mathbf{C} = \overline{\mathbf{W}}\,\overline{\mathbf{N}}$$

where the aggregate disutilities of labor supply are given by,

$$\overline{\mathbf{N}} := \left[\int_0^1 \overline{N}_j^{\frac{\theta+1}{\theta}} \, \mathrm{d}j\right]^{\frac{\theta}{\theta+1}}, \quad \theta > 0$$

$$\overline{N}_j := \left[\sum_{i=1}^{M_j} n_{ij}^{\frac{\eta+1}{\eta}}\right]^{\frac{\eta}{\eta+1}}, \quad \eta > 0$$

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 $\eta\,(\theta) \to \infty$ firms (markets) become perfect substitutes, the representative household will supply her work only in the firm (market) with the highest wage. On the contrary, as $\eta\,(\theta) \to 0$, firms (markets) become perfect complements, and she will supply the same amount of work in all the markets regardless of the wage offers.

As notation, the bar denotes indexes, which are not directly observable variables, but can be constructed from raw data. For example, $\overline{N}_j$ describes the labor disutility for the representative household for supplying N_j in market j.

Labor supply: Given the distribution of wages $\{w_{ij}\}$, 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:

$$n_{ij} = \left(\frac{w_{ij}}{\overline{W}_j}\right)^{\eta} \left(\frac{\overline{W}_j}{\overline{\mathbf{W}}}\right)^{\theta} \overline{\mathbf{W}}^{\psi} \tag{1}$$

where $\overline{W}_j$ and $\overline{\mathbf{W}}$ are the market and economy wage index respectively, and are defined as follow:

$$\overline{W}_j := \sum_{i=1}^{M_j} w_{ij} n_{ij} \qquad \Rightarrow \overline{W}_j = \left[\sum_{i=1}^{M_j} w_{ij}^{1+\eta}\right]^{\frac{1}{1+\eta}}$$

$$\overline{\mathbf{W}} := \int_0^1 \overline{W}_j \overline{N}_j \,\mathrm{d}j \;\Rightarrow \overline{\mathbf{W}} = \left[\int_0^1 \overline{W}_j^{1+\theta} \,\mathrm{d}j\right]^{\frac{1}{1+\theta}}$$

By inverting equation 1, the inverse labor supply is

$$w_{ij} = n_{ij}^{\frac{1}{\eta}} \overline{N}_j^{\frac{1}{\theta} - \frac{1}{\eta}} \overline{\mathbf{N}}^{\frac{1}{\psi} - \frac{1}{\theta}} \tag{2}$$

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.[12]

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

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 (θ) is high, the individual preferences are closer together, each worker has the same idiosyncratic preference regarding each firm (market). She becomes indifferent on which firm (market) to work for. This increases the competition between firms, as the wage component is the most important in the worker work supply decision. On the other hand, if η (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).

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.

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}) on the market-level wage and labor supply $(\overline{W}_j, \overline{N}_j)$, but they take as given the economy-aggregate wage and labor supply $(\overline{\mathbf{W}}, \overline{\mathbf{N}})$. In order to maximize profits, firms choose the number of workers to hire (n_{ij}).[13]

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

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

[13]For the sake of simplicity, I assumed that labor is the only input, but the model can be easily extended to include capital.

s.t.

$$\begin{cases} w_{ij} = n_{ij}^{\frac{1}{\eta}} \overline{N}_j^{\frac{1}{\theta}-\frac{1}{\eta}} \overline{\mathbf{N}}^{\frac{1}{\psi}-\frac{1}{\theta}} \\ \overline{N}_j = \left[\sum_{i=1}^{M_j} n_{ij}^{\frac{\eta+1}{\eta}}\right]^{\frac{\eta}{\eta+1}} \end{cases}$$

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

Therefore, by solving the firm profit maximization problem with respect to n_{ij},

$$\gamma \alpha z_{ij} (n_{ij}^{\gamma})^{\alpha-1} n_{ij}^{\gamma-1} = w_{ij} + \frac{\partial w_{ij}}{\partial n_{ij}} n_{ij}$$

which can be written as,

$$MPL_{ij} = (1 + \epsilon_{ij}) w_{ij} \tag{3}$$

where ϵ_{ij} is the inverse labor supply wage elasticity $((\frac{\partial w_{ij}}{\partial n_{ij}} \frac{n_{ij}}{w_{ij}}))$ and MPL is the marginal productivity of labor:

$$MPL_{ij} = \gamma \alpha z_{ij} (n_{ij}^{\gamma})^{\alpha-1} n_{ij}^{\gamma-1} \tag{4}$$

Therefore, the wage at firm i depends on both its markdown $((1 + \epsilon_{ij}))$ and the marginal productivity of labor. The latter depends by the firm productivity level z_{ij} and the number of employees (n_{ij}).

More interesting is to analyze how the firm-specific markdown changes. Since each firm competes strategically within a market, i.e. it maximizes its profits taking into account the labor demand of its competitors within the same market. From equation 2

$$\frac{1}{\varepsilon_{ij}} := \frac{\mathrm{d}\log(w_{ij})}{\mathrm{d}\log(n_{ij})} = \frac{1}{\eta} + \left(\frac{1}{\theta} - \frac{1}{\eta}\right) \frac{\mathrm{d}\log(\overline{N}_j)}{\mathrm{d}\log(n_{ij})} + \left(\frac{1}{\psi} - \frac{1}{\theta}\right) \frac{\mathrm{d}\log(\overline{\mathbf{N}})}{\mathrm{d}\log(n_{ij})}$$

Given that the firms do not compete strategically outside their own market, they take as given the aggregate level, i.e. $\frac{\mathrm{d}\log(\mathbf{N})}{\mathrm{d}\log(n_{ij})} = 0$. While,

$$\frac{\mathrm{d}\log(\overline{N}_j)}{\mathrm{d}\log(n_{ij})} := \frac{\partial \overline{N}_j}{\partial n_{ij}} \frac{n_{ij}}{\overline{N}_j} = \left(\frac{n_{ij}}{\overline{N}_j}\right)^{\frac{1}{\eta}} \frac{n_{ij}}{\overline{N}_j} = (s_{ij})^{\frac{1+\eta}{\eta}} = \tilde{s}_{ij}$$

Therefore, we can write the Nash equilibrium labor elasticity as a function of the (within, across) elasticities (η, θ) and the employment-share of firm i in market j as

$$\epsilon_{ij} = \frac{1}{\eta}(1 - \tilde{s}_{ij}) + \frac{1}{\theta}\tilde{s}_{ij} \tag{5}$$

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.

Proposition 1. *Given $\eta > \theta$, both the inverse labor supply elasticity increases and the markdown increases with the employment share.*

$$\frac{\partial \epsilon_{ij}}{\partial s_{ij}} > 0 \qquad\qquad \frac{\partial \mu_{ij}}{\partial s_{ij}} > 0$$

Under the assumption that workers are more willing to change firm than market ($\eta > \theta$), in equilibrium the inverse labor supply elasticity is increasing with the employment share ($\frac{\partial \epsilon_{ij}}{\partial s_{ij}} > 0$), consequently also the markdown is increasing ($\frac{\partial \mu_{ij}}{\partial s_{ij}} > 0$). Therefore, the larger a firm is, the more expensive it is to hire new workers, but at the same time the higher is the returns it extracts from worker productivity. 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. While, relative small firms can more easily poach workers from their competitors, since the movement costs within a market are smaller than across markets.

3.2 Including endogenous training investment decision

Building on this framework, I introduce the possibility for employers to invest in training. Specifically, training increases the workers productivity. Thus, in order to maximize profits, firms choose not only the number of workers to hire (n_{ij}), but also how much to invest in their human capital (h_{ij}). Contrary to the wage, he cost for training (τ) is considered exogeneous and linear in the level of human capital. Then, hte new profit maximization problem is the following,

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

s.t.

$$\begin{cases} \overline{w}_{ij} = \textit{inverse labor supply} \\ \overline{N}_j = \textit{disutility working in market } j \end{cases}$$

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, I assume that training as two additional effects. On the one hand, higher level of training in market decreases the disutility for working in that market, on the other hand, a relative higher investment in training increases the disutility of working for that firm.

The rationale behind this is that each market has a specific set of skills for the jobs in that market. Thus, by moving from a market to another, workers are requested to learn these new skills. If the market level of training in that market is high, the amount of effort a worker has to do to apprehend these new skills is lower, reducing, as a consequence, the cost of moving into that market. On the other hand, within a market, the 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. Formally, the aggregate disutilies of labor supply become:

$$\begin{aligned} N_j &:= \left[\sum_{i=1}^{M_j} n_{ij}^{\frac{\eta+1}{\eta}}\right]^{\frac{\eta}{\eta+1}} G(H_j)^{-1} \qquad , \quad G(H_j) > 0, \quad \forall H_j \\ n_{ij} &:= \overline{n}_{ij} g(h_{ij}) \,, \qquad\qquad\qquad\qquad\qquad g(h_{ij}) > 0, \quad \forall h_{ij} \end{aligned}$$

Analogous to what done in subsection 3.1, solving the representative household problem gets the following inverse labor supply

$$\overline{w}_{ij} = \overline{n}_{ij} g(h_{ij})^{\frac{1+\eta}{\eta}} \overline{N}_j^{\frac{1}{\theta}-\frac{1}{\eta}} G(H_j)^{-\frac{1}{\theta}} \mathbf{N}^{\frac{1}{\psi}-\frac{1}{\theta}} \tag{6}$$

Then, assuming the firm will choose the optimal level of investment given the labor demand ($h_{ij}(\overline{n}_{ij})$), solving the new firm profit maximization problem given equation 6 gives the following key equations

$$\begin{aligned}
&MPL_{ij} = (1+e_{ij})\overline{w}_{ij} \\
&e_{ij} = (1-\tilde{s}_{ij})\frac{1}{\eta} + \tilde{s}_{ij}\frac{1}{\theta} + \frac{\partial log(g(h_{ij}))}{\partial log(\overline{n}_{ij})}\left[\frac{1+\eta}{\eta} - \frac{1}{\theta}\frac{\partial log(G(H_j))}{\partial log(g(h_{ij}))}\right]
\end{aligned} \tag{7}$$

$$\frac{\partial log(G(H_j))}{\partial log(g(h_{ij}))} = \underbrace{\frac{\partial G(H_j)}{\partial H_j}\frac{H_j}{G(H_j)}\frac{\partial H_j}{\partial h_{ij}}\frac{h_{ij}}{H_j}}_{\varepsilon_R}\left(\underbrace{\frac{\partial g(h_{ij})}{\partial h_{ij}}\frac{h_{ij}}{g(h_{ij})}}_{\varepsilon_S}\right)^{-1}$$

where ε_R and ε_S are respectively the *recruitment* labor elasticity and *separation* labor elasticity induced by training. In other words, how much the labor supply changes by an increase in the investment in training. On the one hand, by increasing the disutility for working in the same firm, it increases the separation rate; on the other hand, by decreasing the disutility for working in that market, it also increases the recruitment rate.

Therefore, one can expect that the larger is an employer in a local labor market the larger becomes the recruitment elasticity with respect to the separation elasticity. Up to a point where the last addend in the right hand side of equation 7 becomes negative, thus the employer by increasing the investment in training can decrease the inverse labor supply elasticity, i.e. how much she pays to hire an additional unit of labor.

Empirical Predictions:
Assuming that $\eta > \theta$, an increase in the local labor market concentration (employment share) leads to the following predictions:

1. A direct negative effect on wages
2. An increase in the investment for training employees
3. An improvement of workers' productivity
4. A decline in the training-induced increase in wage

To recap, the conceptual framework developed in this section illustrates how an increase in the local labor market concentration can induce a negative direct effect on wages and a positive direct impact on training investment. Two elements drive the latter. First, training increases the workers' productivity which is extracted by employers given their labor market power. Second, because dominant employers, by increasing training, can increase the recruitment rate without drastically increasing the wages and without the threat of seeing their employees poached by competitors. As this second element becomes prominent, training loses its productivity enhancement objective for its recruitment objective. Thus, at high concentration levels, training produces less return in terms of increase in productivity and wages.

4 Data

4.1 US Data

The data comes from two different sources: Survey of Income and Program Participation (SIPP) and the County Business Pattern (CBP).

Labor Market Concentration Data

The labor market concentration data comes from the County Business Pattern (CBP).[14] CBP is an annual data series that provides information on employment, establishment size distribution, and payroll by county and industry. It covers all U.S. employment except self-employed individuals, employees of private households, railroad employees, agricultural production employees, and most government employees. In particular, I extract the CBP database for the years 1988 and 2002. Unfortunately, CBP does not disclose information on individual employers, and information on employment by county and industry is sometimes reported as an interval instead of an exact count. I adopt the procedure developed in Autor et al. (2013), to impute through a fixed point algorithm the number of employees for each establishment that has an interval censored number of employees. Moreover, over

[14] The data are available at: https://www.census.gov/data/datasets/2008/econ/cbp/2008-cbp.html

the years, CBP adopts different industry codes, it switches from SIC 1987 to NAICS 1997. Although they are closely related, it is not possible to create a one to one crosswalk at the most detailed definition (6 digits), except through a probabilistic imputation. Therefore, I adopt the most conservative approach and I aggregate all the industry code at the NAICS 2-digit level, which allows a precise crosswalk between the two code structures and the ones used by the SIPP.[15] Moreover, SIPP surveys do not provide information on the county where the workers live or work, but they provide only the Metropolitan Statistical Area (MSA), which is also provided by CBP. Consequently, I define a (local labor) market as the combination of a 2-digit NAICS code and a MSA. The labor market concentration for each of those markets m is

$$HHI_m = \sum_{i=1}^{N_m} s_{im}^2$$

where s_{im} is the share of employment for the establishment i in market m and N_m is the number of establishment in market m.

Training Data

The training data comes from the Survey of Income and Program Participation (SIPP) for the years 1990, 1991, 1992, 1993, 1996, and 2001, which provide rich information both on the individual characteristics and working conditions. In particular, from these surveys I extract information on training, wages, and other worker's characteristics, such as gender, age, education, race.[16] SIPP is a longitudinal survey that interviews respondents once every for months. The surveys are divided into Topical and Core modules, Core modules repeats the same questions in each interview round, while the Topical modules are asked only once per survey series.[17] Unfortunately, the training questions are asked in the Topical Module 2, hence, they are asked only once for each of the survey series. Therefore, with regards to training I cannot exploit the SIPP panel structure, but I can pooled the data from the

[15] SIPP uses the US Census code 1980 or 1990 as industry code.

[16] There are also more recent SIPP surveys: 2004, 2008, 2014, and 2018. However, unfortunately, these surveys do not disclose the metropolitan statistical area of the workers, but only their state. Therefore, these surveys cannot be use to investigate the effects of local labor market concentration on training and wages. Moreover, there are other characteristics that I will like to include as controls, in particular, the worker's experience, tenure, occupation and whether the worker is employed in a small or large firm or if she is a member of a labor union. Unfortunately, this information is not homogeneous between the various surveys: occupation changes its codification over the years, while information on tenure, experience, firm size, and union for SIPP 1992 and 1993 are reported in a different Topical Module, so there is a temporal discrepancy with information on training provision. I am currently working on how to fix these problems.

[17] The number of modules and their composition change between survey series.

different surveys into a repeated cross-sectional data.

The survey contains several questions about training experience. In particular, my main dependent training variable is an indicator equal to one if the respondent reports to have received a training experience, which did not consist in job search assistance, in the past year and if the cost of the training was borne by the employer.[18]

After merging the two database CBP and SIPP, I restrict the sample to workers who hold only one job and work full time, who are younger than 55 and older than 21, as well as workers who work in for-profit firms in the private sector, excluding the agricultural sector. The final sample for the wage analysis has $1,698,374$ observations, while that for the training analysis $52,264$.[19] Table 1 shows the summary statistics for the two samples. Around 15% of the training sample reports to have received firm-sponsored training in the previous year. The two samples share the same average HHI 182, which is however rather low compared to the literature. By way of comparison, in the literature they find an average HHI that goes around 1000 to 3000. The reasons is that all of them used a more finer definition of local labor market. They use 3 or even 6 digits of the industry code, and as geographic reference they use commuting areas or the county. While, in this paper the local labor market is defined as a combination of a metropolitan statistical area and a 2-digit industry code. In addition to the clearer broader definition of a 2-digit figure compared to a 3 or 6-digit industrial code, metropolitan statistical areas are also less concentrated than commuting areas, in fact even if in principle they are similar, commuting areas also include rural areas, while metropolitan statistical areas do not. By virtue of this, although the concentration estimated in this paper can be underestimated, it can still be considered as a conservative measure. In any case, the results on the wages are in line with the literature.

[18]The questions are always in the Topical Module 2. For the surveys series of 1996 and 2001, the questions are "During the past year, has [the respondent] received any of the kind of training intended to improve skill in one's current or most recent job?", which corresponds to the variable ERCVTRN2 and "Who sponsored or paid for the most recent training?", which is the variable EWHOTRN2. While for the SIPP 1990,1991,1992,1993 the questions are "Have you ever received training designed to help find job, improve job skills or learn new job?" (TM8446), "Was type of training program was this?" (TM8466), "Who paid for this [training] program?" (TM8508), then TM8498 and TM8500 ask when the respondent received this training. The fact that in different years were asked different questions does not constitute a relevant problem, since this difference is controlled through the use of year-fixed effects.

[19]Remember that unfortunately the training question is asked only once per SIPP series.

Table 1: Summary Statistics for the Full and Training Sample

	Full Sample	Training Sample
Observations	1,698,374	52,264
HHI	182	182
Training	na	0.15
log(wage)	7.74	7.72
Age	37.5	37.1
Female	0.45	0.44
Graduated	0.32	0.31
Married	0.60	0.60

4.2 Italian Data

In addition to the US data, I exploit Italian data to investigate the local labor market concentration from the firm perspective rather than the worker one. In particular, the Italian data comes from two different sources: AIDA (Analisi Informatizzata Delle Aziende) database from 2013 to 2018 and RIL (Rivelazione Longitudinale su Imprese e Lavoro) survey of 2015. The AIDA database contains the full balance sheet and income statement of Italian firms, constructed on the mandatory national registry of firms held by the Italian Chambers of Commerce. I use this database to compute the concentration level (HHI) at the region and ATECO 3-digits industry level.[20] The RIL survey instead provides rich information for 30,000 Italian firms, in particular the information that I use is how much each firm spends in training activities.

5 Empirical strategy

The theory in Section 3 suggests that labor market concentration should have (i) a direct negative effect on wages, (ii) a positive direct effect on training, and (iii) an indirect positive effect on wages through the increase in training. In order to empirically investigate these

[20] ATECO is the italian industry code classification comparable to the US NAICS classification.

results, I estimate the following models at the worker-level:

$$\begin{aligned}
T_{im} &= \beta_1 \log(HHI_m) + \alpha X_{mi} + \mu_s + \mu_y + \mu_c + \varepsilon_{im} \\
\log(w_{im}) &= \beta_2 \log(HHI_m) + \alpha X_{im} + \mu_y + \mu_s + \mu_c + \varepsilon_{im} \\
\log(w_{im}) &= \beta_3 \log(HHI_m) + \beta_4 T_{im} + \beta_5 (\log(HHI_m) \times T_{im}) + \alpha X_{im} + \mu_s + \mu_y + \mu_c + \varepsilon_{im}
\end{aligned}$$

where T_{mi} refers to an indicator for worker i in (MSA-industry) market m having received firm-sponsored training, $\log(HHI_m)$ is the natural logarithm of the HHI index for market m,[21], $log(w_{im})$ is the average annual monthly wage of worker i, μ_y, μ_s, and μ_c are respectively year (y), industry (s), and metropolitican statistical area (c) fixed effects; finally X_{mi} are the observable worker characteristics, i.e. age, gender, education, married, race.[22] It is important to include these controls in order to avoid potential endogeneity bias due to omitted variables.

All estimations are weighted by the worker's SIPP personal weights. Standard errors are clustered at the market level. The coefficient of interests are the β, which capture the effect of higher labor market concentration on the employers' training decision, wages, and the interaction term.

Assuming the changes in the labor-market concentration are mean independent of changes in average unobserved influences on training decision or wages conditional on X and the fixed effects, the regressions identify the parameters of interest (β).

Endogeneity Threat

As for any non-experimental analysis, concerns arise about endogeneity. The major threat of the identification strategy is the occurrence of market-specific shocks that affect both concentration, wages and training. In this regard, I use a so-called Hausman-Nevo instrument (see Hausman (1996) and Nevo (2001)). Specifically, I instrument the variation in a

[21] The HHI are multiplied by 10,000 in order to have positive logarithms, this practice is common in the literature and also use by the Federal Trade Commission of the Department of Justice.

[22] The idea is to introduce other controls, in particular establishment size, union, occupation, experience and tenure. However, for the SIPP 1992 and 1993 these variables are provided in another Topical modules, therefore there is a temporal mismatch between these variables and training information. Regarding occupation, the code used to define it changes over CBP and SIPP years. I am currently working on how to fix these problems.

local market concentration with the average changes in concentration for the same industry but in other geographical areas.

$$log(HHI^{instr.})_{ysc} = log(\frac{1}{M-1}\sum_{k\neq c} HHI_{ysk})$$

where M is the number of geographical areas, y is the year, s is an industry, nd $c(k)$ denotes a geographical area.

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 Autor et al. (2013), Rinz (2018), Qiu and Sojourner (2019), Azar et al. (2020a), and Marinescu et al. (2021).

6 Results

Consistent with previous studies, Table 2 shows a significant and small negative effect of the log HHI on log wages. Column (4) estimates an elasticity of -0.01. Although the elasticity is smaller, it is broadly in line with the literature. By way of comparison, for example Rinz (2018) and Azar et al. (2020a) find an elasticity of respectively -0.09 and -0.16. However, it is worth noticing that they use a finer definition of local labor markets. Hence, they have a larger mean value of HHI.[23] Considering the same increase in the HHI of 200, which in my model consist of an increase of around 100 log points, while in Azar et al. (2020a) of only 10 log points, this leads to a decline in wages of around 0.7%.[24] In the appendix, Table 8 shows the estimates using the IV approach, as in Rinz (2018), where the HHI is instrumented by the average HHI for the same industry in the other geographical areas; the results are in line with the OLS estimates in Table 2.

[23]In this paper, a combination of a 2-digit industry and metropolitan statistical area constitutes a local labor market, while in their papers it is a combination of a 6-digit occupation or 4-digit industry and a commuting zone. So not only my industry classification is more broader, but also a commuting zone contrary to MSA includes also rural areas, which generally have higher level of concentration. This different definition leads that I have a significant lower level of concentration. Indeed, they have an average HHI of around 2000, while in this paper the average HHI is around 200.

[24]According to the U.S. Department of Justice/Federal Trade Commission (DOJ/FTC) (2010) an increase in the HHI of between 100 points and 200 points potentially raise significant competitive concerns and often warrant scrutiny.

Table 2: Effect of labor market concentration on wages

log(wage)	(1)	(2)	(3)	(4)
log(HHI)	-0.0472***	-0.00439	-0.0492***	-0.00864**
	(0.00645)	(0.00481)	(0.00470)	(0.00431)
(5) Controls		✓	✓	✓
(13) Year FE	✓	✓	✓	✓
(17) NAICS FE			✓	✓
(97) MSA FE				✓
Observations	1,698,374	1,698,374	1,698,374	1,698,374
MDV	7.73	7.73	7.73	7.73
R^2	0.138	0.313	0.374	0.388

Notes: standard error in parenthesis, clustered at industry × MSA level. Table reports OLS regression estimates of the effect of local labor market concentration, measured by the HHI, on log average annual monthly wage, from 1990 to 2012. Controls are age, education, married, gender, and race. Columns represent separate regressions, which include the indicated fixed effects and controls variables. As a log-log model, coefficients denotes elasticities. MDV stands for mean dependent variable.

Table 3 presents the effects of HHI on training. Column (4) shows that an increase in the HHI of 1 log point increases the probability of being trained of almost 0.01 percentage point, which consists of an increase of 0.06%. However, by considering the same increase of 200 HHI, the probability to be trained increases of 2.1%.[25] As mentioned above, training analysis is done on a smaller sample, as SIPP respondents provide training information only once for survey series. Therefore, for completeness, Table 9 reports the same estimates of Table 2 on this smaller sample.

In Table 4, I report the OLS estimates of the model with the interaction between log HHI and training. Considering column (4), if a worker has received training her wage increases by around 30%. While, an increase of 1 log point in the HHI leads to a decrease in wages of about 0.01 log points. Thus, an increase of 200 HHI is associated with a decline in wages of around 0.6%. Finally, the term of interaction shows that when a worker is trained, the induced increase in wages decreases with the level of concentration in the market. In particular, if the local labor market concentration increases by 200 HHI, the wage for

[25]This results should be take very cautiously, because the linear probability model has some limitations, especially when considering large changes in the independent variable. In particular, it assumes a linear effect of the independent variable, which can lead the predicted probability to be outside the $[0, 1]$ interval, which is clearly problematic.

Table 3: Effect of labor market concentration on firm sponsored training

training	(1)	(2)	(3)	(4)
log(HHI)	0.0139***	0.0137***	0.0130***	0.00961***
	(0.00247)	(0.00152)	(0.00233)	(0.00313)
(5) Controls		✓	✓	✓
(6) Year FE	✓	✓	✓	✓
(17) NAICS FE			✓	✓
(97) MSA FE				✓
Observations	52,264	52,264	52,264	52,264
MDV	0.15	0.15	0.15	0.15
R^2	0.083	0.083	0.092	0.104

Notes: standard error in parenthesis, clustered at industry × MSA level. Table reports linear probability regression estimates of the effect of local labor market concentration, measured by the HHI, on receiving firm sponsored training the previous year. Since training occured the previous year, also the HHI refers to the year before the interview. Years 1990, 1991, 1992, 1993, 1996, and 2001. Controls are age, education, married, gender, and race. Columns represent separate regressions, which include the indicated fixed effects and controls variables. As a lin-log model, coefficients denotes percentage points increase. MDV stands for mean dependent variable.

a trained worker declines by 1.7%. As a preliminary result, Table 10 reports the results including as control whether the worker is employed in a large firm and if she is member of a labor union, the results are in line with the ones in Table 4.

7 Results on Italian data

In the appendix, Table 11 displays the distribution of the HHI at the region and province level for the Italian data for different industry specification, from 1 to 5 digits ATECO industry code. Moreover, I perform the same exercise done for the US data on the Italian data regarding concentration and wages. In particular, Table 12 and Table 14 show the results of the OLS regression at different level of industry classification and at the province and region level respectively. The results are in line with what found in the US analysis. Also the IV regressions on the Italian data corroborate the results obtained in the US data, see Table 13 and Table 15.

Table 4: Effect of labor market concentration on firm sponsored training and wages

log(wage)	(1)	(2)	(3)	(4)
training	0.363***	0.304***	0.263***	0.263***
	(0.0310)	(0.0229)	(0.0243)	(0.0238)
log(HHI)	-0.0488***	-0.00521	-0.0507***	-0.00911*
	(0.00684)	(0.00494)	(0.00514)	(0.00516)
train. × log(HHI)	-0.0324***	-0.0263***	-0.0218***	-0.0232***
	(0.00598)	(0.00472)	(0.00466)	(0.00473)
(5) Controls		✓	✓	✓
(6) Year FE	✓	✓	✓	✓
(17) NAICS FE			✓	✓
(97) MSA FE				✓
Observations	52,264	52,264	52,264	52,264
MDV	7.72	7.72	7.72	7.72
R^2	0.170	0.345	0.406	0.419

Notes: standard error in parenthesis, clustered at industry × MSA level. Table reports OLS regression estimates of the effect of local labor market concentration, measured by the HHI, having received a firm sponsored training the previous year, and their interaction on the log average annual monthly wage. Since training occurred the previous year, also the HHI refers to the year before the interview. Years 1990, 1991, 1992, 1993, 1996, and 2001. Controls are age, education, married, gender, and race. Columns represent separate regressions, which include the indicated fixed effects and controls variables. MDV stands for mean dependent variable.

In addition to the US data, the Italian data provides information on how each firm invests in the training of its workforce. Table 5 regresses the log of the total amount invested by a firm in training on the log of the HHI, measured at the 3-digit ATECO and region level. It shows that an increase of 1% of HHI, which consists of an increase of around 5 HHI points, increases the investment in training between 0.06% to 0.09%. This result is at odds with what showed in Section 3, since the total investment in training should decrease with the increase in concentration. However, first these are very preliminary results and second when we substitute the HHI with the employment share of each firm this negative correlation between concentration and total training arises, see Table 16.

Finally, Table 6 shows a significant and positive effect of concentration on the per-worker investment in training, which is computed dividing the total amount of investment for the number of employees. Table 17 performs the same analysis using the employment share rather than the HHI.

Table 5: Effect of labor market concentration on total training investment

log(Cost)	(1)	(2)	(3)	(4)	(5)
log(HHI)	0.0944***	0.0519***	0.0327	0.0554***	0.0668**
	(0.0119)	(0.0102)	(0.0210)	(0.0181)	(0.0268)
log(employees)		0.6931***		0.7274***	0.7566***
		(0.0125)		(0.0136)	(0.0523)
interaction					-0.0054
					(0.0094)
(205) Industry FE			✓	✓	✓
(20) Region FE			✓	✓	✓
Observations	8,810	8,803	8,793	8,786	8,786

Notes: clustered standard error in parenthesis. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification.

Effect of Labor Market Concentration on Productivity

I now consider the impact of labor market concentration on workers productivity. I measure workers productivity as the ratio between valued added and the total firm expenditure in wages and salaries, which is a practical indicator of the overall workforce efficiency. Both variables are included in the firm balance sheet collected in the AIDA database. Since we do not need the RIL data for this analysis, Table 7 provides the OLS estimates for the entire Italian AIDA sample with the preferred specification that includes industry 3-digit ATECO code, province (or region), and year fixed effects. Columns (1) shows the OLS estimates of regional labor market concentration on workers' productivity, Column (2) controls also for the log of the number of employees in that firm, Columns (3-4) repeat the same analysis but using the concentration at the province level.

The results presented in Table 7 are in line with the basic prediction of the model: labor market concentration is positively related with the workers' productivity level. This can be seen across all the four specifications where all the coefficients are statistically significant at at least 10% level. In particular, a 10% increase of the labor concentration leads to an increase that goes from 7 (Column 4) to 18 (Column 1) percentage points , which consists

Table 6: Effect of labor market concentration on per-worker training investment

log(perworker cost)	(1)	(2)	(3)	(4)	(5)
log(HHI)	0.0341***	0.0527***	0.0650***	0.0567***	0.0652**
	(0.0106)	(0.0103)	(0.0187)	(0.0183)	(0.0271)
log(employees)		-0.3040***		-0.2697***	-0.2479***
		(0.0126)		(0.0137)	(0.0529)
interaction					-0.0041
					(0.0095)
(205) Industry FE			✓	✓	✓
(20) Region FE			✓	✓	✓
Observations	8,803	8,803	8,786	8,786	8,786

Notes: clustered standard error in parenthesis. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification.

in an increase of 0.8% and 2.15% respectively.

8 Conclusions

This paper provides evidence on the effects of local labor market concentration on wages and training. First, I confirm the literature results of a significant negative effects of local labor market concentration on wages: workers that would move to a market that is more concentrated for 200 HHI could see their wages fall by almost 1%.[26] The latter result supports the idea in the literature that employer market power is an important but not necessarily the main driver of wage inequality. However, as a second result, I also show that labor market concentration has a significant positive effect on firm sponsored training provision and that trained workers get some returns from their increased productivity, even if these returns decrease with the level of concentration. This suggests that by increasing the returns that firms can extract from workers productivity, a high local labor market concentration might lead to more firm-provided training and, possibly, to higher labor productivity. Finally, these findings provide an additional explanation for why the wage-concentration elasticities are particularly small, underlining the importance of taking into

[26]According to the U.S. Department of Justice/Federal Trade Commission (DOJ/FTC) (2010) guidelines, a merger that increases the HHI by 200 raises competitive concerns and should be monitored.

Table 7: Effect of labor market concentration on workers productivity

Productivity	(1)	(2)	(3)	(4)
log(HHI)	4.329**	1.685*	3.114*	1.637**
	(1.857)	(0.863)	(1.795)	(0.835)
log(employees)		–0.513		–0.454
		(0.644)		(0.642)
(6) Year FE	✓	✓	✓	✓
(324) Industry FE	✓	✓	✓	✓
(106) Province FE	✓	✓		
(20) Region FE			✓	✓
Observations	2,287,959	2,254,206	2,288,191	2,254,206

Notes: clustered standard error in parenthesis, * p ¡ 0.10, ** p¡0.05, *** p¡0.01.

Table reports OLS regression estimates of the effect of local labor market concentration, measured by the HHI, on the workers productivity, measured as the ratio between value added over firm's expenditurefor wages and salaries. All the regressions include fixed effects for year, industry, province (or region). As a lin-log model, coefficients denotes percentage points changes.

account the indirect positive effects that concentration can have on wages, in particular through training. As this paper shows, these factors can potentially bias downward any existing negative effect of concentration on wages when such indirect channels are not taken into account.

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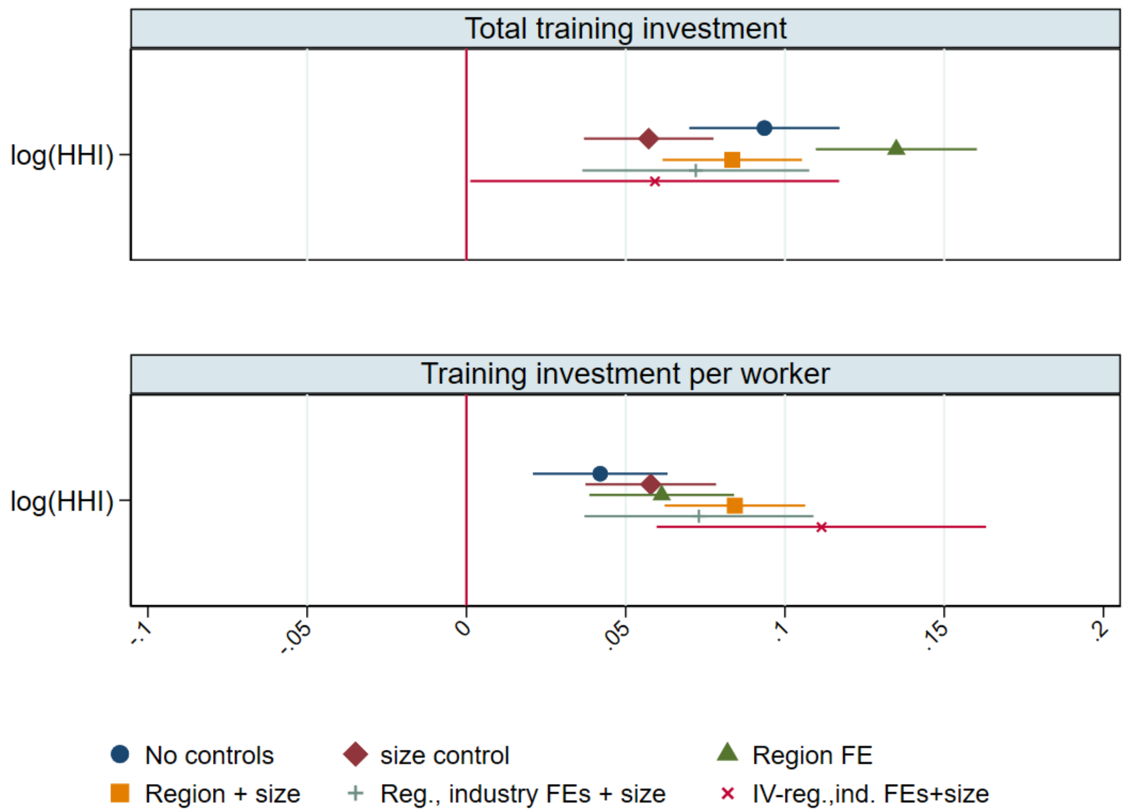
9 Appendix

Table 8: Effect of labor market concentration on wages, IV approach

log(wage)	(1)	(2)	(3)	(4)
log(HHI)	0.0928***	0.0491***	-0.0186	-0.0204*
	(0.00832)	(0.00637)	(0.0124)	(0.0121)
(5) Controls		✓	✓	✓
(13) Year FE	✓	✓	✓	✓
(17) NAICS FE			✓	✓
(97) MSA FE				✓
Observations	1,698,374	1,698,374	1,698,374	1,698,374
MDV	7.73	7.73	7.73	7.73
R^2	0.138	0.313	0.374	0.388

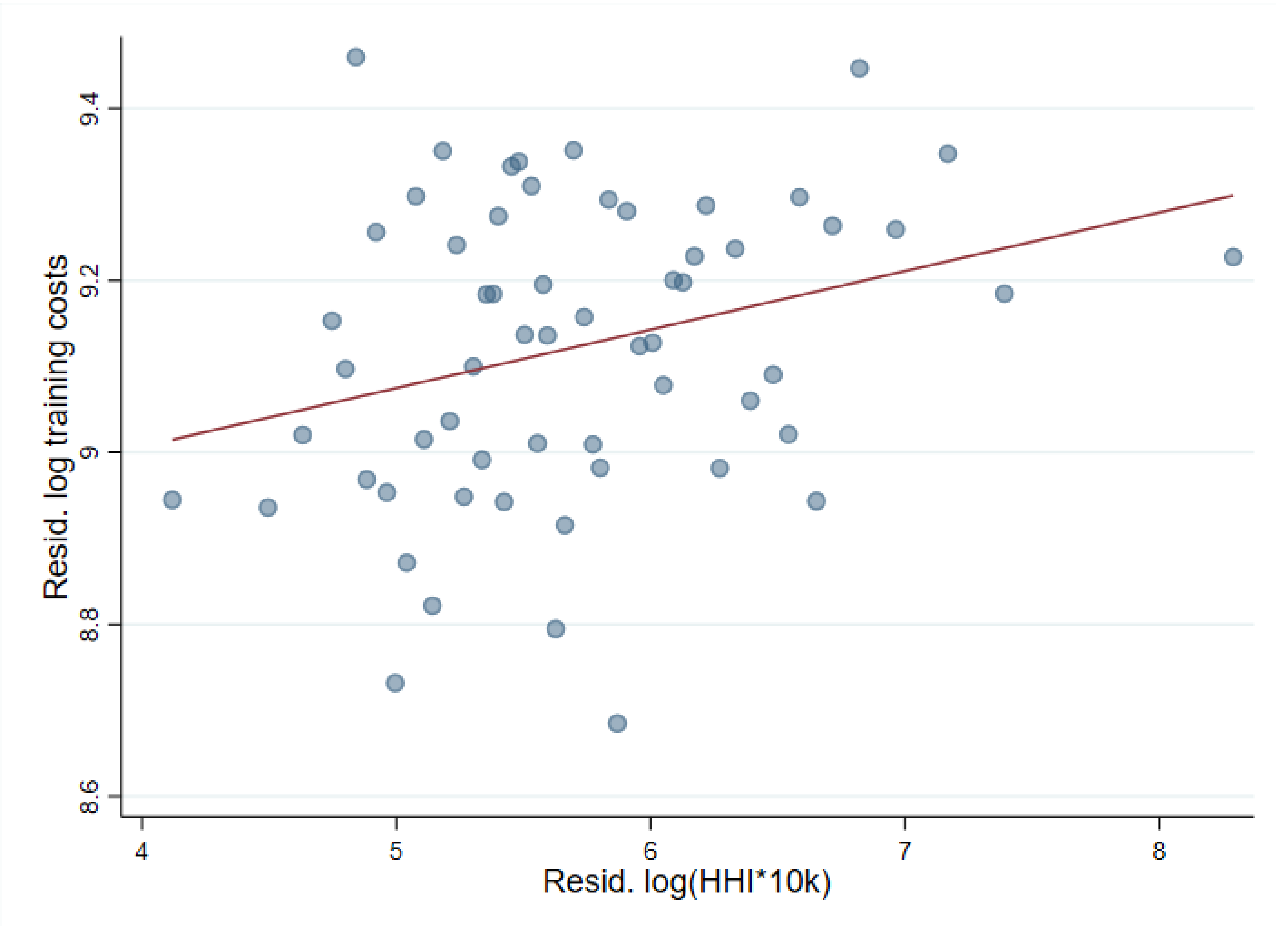
Notes: standard error in parenthesis, clustered at industry $\times$ MSA level. Table reports IV regression estimates of the effect of local labor market concentration, measured by the HHI, on log average annual monthly wage, from 1990 to 2012. The instrument consists in the average log HHI for the same industry but in a different MSA. Controls are age, education, married, gender, and race. Columns represent separate regressions, which include the indicated fixed effects and controls variables. As a log-log model, coefficients denotes elasticities. MDV stands for mean dependent variable.

Figure 1: Coefficients of training investments on HHI regressions



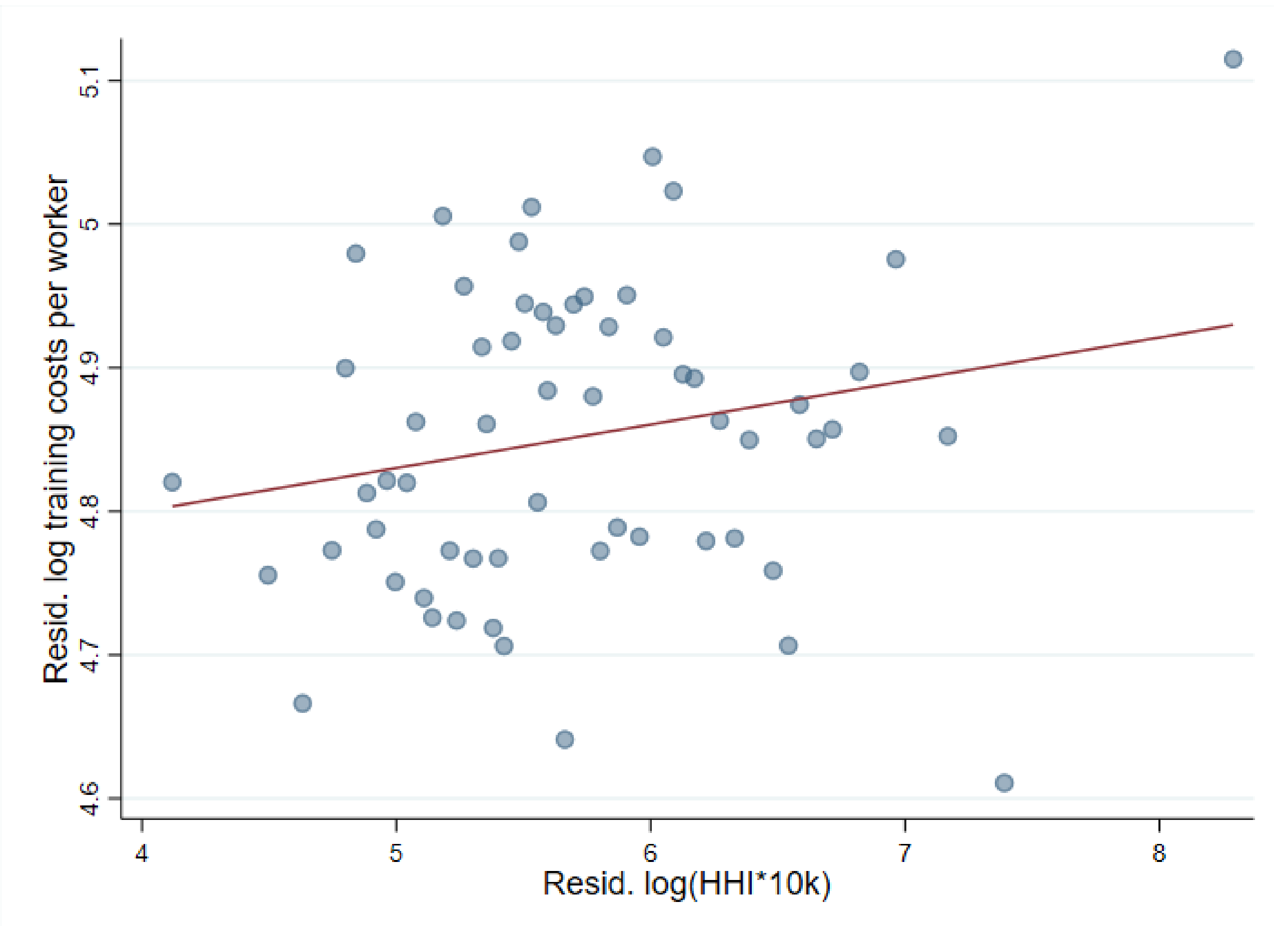
Note: This Figure plots the OLS and IV estimates of local labor market employment concentration on either total or per-worker training investment on the Italian data.

Figure 2: Binnerscatter plot, residualized regression of labor market concentration and total training investment



Note: The residuals are computed using as regressors industry 3-dig, region,and number of employees. Italian data.

Figure 3: Binnerscatter plot, residualized regression of labor market concentration and per-worker training investment



Note: The residuals are computed using as regressors industry 3-dig, region,and number of employees. Italian data.

Table 9: Effect of labor market concentration on wages in the training sample

log(wage)	(1)	(2)	(3)	(4)
log(HHI)	-0.0491***	-0.00616	-0.0511***	-0.0108**
	(0.00685)	(0.00491)	(0.00508)	(0.00498)
(5) Controls		✓	✓	✓
(6) Year FE	✓	✓	✓	✓
(17) NAICS FE			✓	✓
(97) MSA FE				✓
Observations	52,264	52,264	52,264	52,264
MDV	7.72	7.72	7.72	7.72
R^2	0.148	0.330	0.394	0.408

Notes: standard error in parenthesis, clustered at industry × MSA level. Table reports OLS regression estimates of the effect of local labor market concentration, measured by the HHI, on log average annual monthly wage. Years 1990, 1991, 1992, 1993, 1996, and 2001. Controls are age, education, married, gender, and race. Columns represent separate regressions, which include the indicated fixed effects and controls variables. As a log-log model, coefficients denotes elasticities. MDV stands for mean dependent variable.

Table 10: Effect of labor market concentration on training and wages, controlled for large firms

log(wage)	(1)	(2)	(3)	(4)
training	0.369***	0.300***	0.253***	0.247***
	(0.0323)	(0.0216)	(0.0236)	(0.0227)
log(HHI)	-0.0464***	-0.00850*	-0.0449***	-0.00629
	(0.00745)	(0.00495)	(0.00536)	(0.00524)
train. × log(HHI)	-0.0334***	-0.0290***	-0.0225***	-0.0224***
	(0.00622)	(0.00458)	(0.00472)	(0.00464)
(7) Controls		✓	✓	✓
(4) Year FE	✓	✓	✓	✓
(17) NAICS FE			✓	✓
(97) MSA FE				✓
Observations	32,703	32,703	32,703	32,703
MDV	7.78	7.78	7.78	7.78
R^2	0.168	0.346	0.404	0.417

Notes: standard error in parenthesis, clustered at industry × MSA level. Table reports OLS regression estimates of the effect of local labor market concentration, measured by the HHI, having received a firm sponsored training the previous year, and their interaction on the log average annual monthly wage. Since training occurred the previous year, also the HHI refers to the year before the interview. Years 1990, 1991, 1992, 1993, 1996, and 2001. Controls are age, education, large firm, unionized, married, gender, and race. Columns represent separate regressions, which include the indicated fixed effects and controls variables. MDV stands for mean dependent variable.

Table 11: HHI market-level distribution with different industry specifications

HHI	Mean	P10	P25	P50	P75	P90	*#geograph.*	*#industries*
Province level								
Ateco 1	1361	109	261	665	1607	3443	107	21
Ateco 2	2914	297	704	1711	4136	8523	107	87
Ateco 3	4447	610	1415	3438	7341	10000	107	332
Ateco 4	5502	1086	2335	5000	10000	10000	107	790
Ateco 5	5986	1387	2840	5556	10000	10000	107	1199
Region level								
Ateco 1	826	39	91	233	661	1933	20	21
Ateco 2	1727	93	242	671	2090	5000	20	87
Ateco 3	3048	210	573	1691	4540	10000	20	332
Ateco 4	3860	399	998	2643	5973	10000	20	790
Ateco 5	4227	523	1260	3145	6800	10000	20	1199

.

Table 12: OLS regression: effect of concentration on average wages (province level)

log(wage)	(1) Ateco 1	(2) Ateco 2	(3) Ateco 3	(4) Ateco 4	(5) Ateco 5
log(HHI)	-0.007***	-0.017***	-0.016***	-0.016***	-0.014***
	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)
Observations	2,691,810	2,691,810	2,691,807	2,691,806	2,691,804
R-squared	0.117	0.139	0.151	0.160	0.167

Table 13: IV regression: effect of concentration on average wages (province level)

log(wage)	(1) Ateco 1	(2) Ateco 2	(3) Ateco 3	(4) Ateco 4	(5) Ateco 5
log(HHI)	-0.234***	-0.252***	-0.419***	-0.313***	-0.205*
	(0.0350)	(0.0230)	(0.0499)	(0.0917)	(0.112)
Observations	2,691,810	2,691,810	2,691,805	2,691,804	2,691,792

All the regressions include year, industry, and province fixed effects. Instrument à la Rinz (2018): the concentration in one local market (industry $\times$ province) is instrumented with the average concentration in the markets with the same industry but in a different province.

Table 14: OLS regression: effect of concentration on average wages (region level)

log(wage)	(1) Ateco 1	(2) Ateco 2	(3) Ateco 3	(4) Ateco 4	(5) Ateco 5
log(HHI)	-0.0081***	-0.0125***	-0.0098***	-0.0115***	-0.0102***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Observations	2,691,810	2,691,810	2,691,807	2,691,806	2,691,804
R-squared	0.111	0.134	0.146	0.154	0.161

Table 15: IV regression: effect of concentration on average wages (region level)

log(wage)	(1) Ateco 1	(2) Ateco 2	(3) Ateco 3	(4) Ateco 4	(5) Ateco 5
log(HHI)	-0.1178***	-0.0652***	-0.0608***	-0.0631***	-0.0573***
	(0.0115)	(0.0069)	(0.0074)	(0.0073)	(0.0075)
Observations	2,691,810	2,691,810	2,691,794	2,691,793	2,691,781

All the regressions include year, industry, and region fixed effects. Instrument à la Rinz (2018): the concentration in one local market (industry $\times$ region) is instrumented with the average concentration in the markets with the same industry but in a different region.

Table 16: Effect of labor market concentration on total training investment (using employment share)

log(Cost)	(1)	(2)	(3)	(4)	(5)
log(share)	0.2834***	0.0357***	0.5746***	-0.0715***	-0.1559***
	(0.0088)	(0.0098)	(0.0129)	(0.0269)	(0.0298)
log(employees)		0.6652***		0.7958***	0.1706**
		(0.0152)		(0.0294)	(0.1000)
interaction					0.0400***
					(0.0061)
(205) Industry FE			✓	✓	✓
(20) Region FE			✓	✓	✓
Observations	8,803	8,803	8,786	8,786	8,786

Notes: standard error in parenthesis. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification.

Table 17: Effect of labor market concentration on per-worker training investment (using employment share)

log(perworker cost)	(1)	(2)	(3)	(4)	(5)
log(share)	-0.0874***	0.0362***	-0.2349***	-0.0715***	-0.1603***
	(0.0082)	(0.0099)	(0.0126)	(0.0272)	(0.0300)
log(employees)		-0.3322***		-0.2013***	-0.8592***
		(0.0154)		(0.0297)	(0.1009)
interaction					0.0421***
					(0.0061)
(205) Industry FE			✓	✓	✓
(20) Region FE			✓	✓	✓
Observations	8,803	8,803	8,786	8,786	8,786

Notes: standard error in parenthesis. Weighted according to the weights provided by the RIL survey, based on regional and industry stratification.