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Essays on Labor Market Competition and On-the-Job Training

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General Introduction

The first chapter studies the effect of employer concentration on the provision of on-the-job training and their combined impact 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 employment concentration they face in a local labor market. High levels of employer concentration reduce both the separation and recruitment wage elasticities. As a result, employers in highly concentrated markets find hiring new workers more challenging, yet losing employees poached by competitors is at the same time more unlikely. On top of increasing workers' productivity, on-the-job training has an ambiguous effect on labor supply elasticities. Testable predictions for training and wages are derived and confronted with comparable microdata on training from Italy. Specifically, I estimate with an instrumental variable approach that high employer concentration in a local labor market (i) positively affects employer-provided training, (ii) reduces wages, and (iii) decreases the productivity returns of training investment. Finally, these findings suggest that using employer concentration as a direct measure of labor market competition underestimates the negative effect of concentration on wages.

The second chapter provides a new set of stylized facts on firm provision of on-the-job training and local labor market competition by exploiting the language used in job vacancies. We take a supervised machine learning approach to identify training offers in more than 12 million US job vacancies. We show our measure correlates well with established on-the-job training measures at the occupation, industry, and regional level. We find that around 20% of job posts offer on-the-job training, with an upward trend over the last decade. Training offers are positively correlated with local labor market concentration, a finding that is robust to an instrumental variables strategy based on the local differential exposure to national firm-level trends. Moving from the first to the third quartile of labor concentration increases training by almost 5%. We interpret our results through the lens of a directed search model where training acts to reduce the queue to fill a vacancy and training has a greater expected benefit to the employer in less competitive labor markets given the lower separation rates.

The third chapter analyses the relationship between labor market concentration and employers' skill demand. Using a novel data set on Italian online job vacancies during 2013-2018 we show that employers in a highly concentrated labor market demand competencies associated with the ability of workers to learn faster (e.g. Social skills) rather than actual knowledge. They also require less experience but higher education. These results are consistent with the hypothesis that employers in more concentrated labor markets are more prone to train their employees. Instead of looking for workers who already have job-specific skills, they look for workers who can acquire them faster and efficiently.

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Chapter 1

Lights and Shadows of Employer Concentration: Wages and Training

1.1 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. 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. 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, it is essential to explore the determinants that stimulate on-the-job training and how labor market concentration could affect them. This is crucial, especially in the aftermath of the Covid-19 pandemic, which 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). 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 the years 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 to measure employment concentration, which is defined as the employment Herfindahl-Hirschman Index (HHI) for 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 a positive and statistically significant effect of employer concentration 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 amount 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 employer concentration and local labor market, the inclusion of 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 on 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. According to the theory, it is unclear whether employer concentration should increase or decrease training provision. Despite increasing worker productivity, training also affects the labor supply elasticity. Specifically, on the one hand, training provision by improving the workers' skills can increase their prospective outside options and, in turn, the probability that other competing firms poach them. 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 retention and attraction rate.[1] The empirical literature confirmed this ambiguous training effect on retention and separation rates, finding results going in both directions.[2] The traditional view on this potential

[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 that have recently quit a job, 45% would have been remained if they were offered more training, while Gallup (2021) observed that 48% of American workers would switch job, if the new job would provide skill training opportunity.

[2] For example, see Munasinghe and O'Flaherty (2005); Jones et al. (2009); Muehlemann and Wolter

ambiguous effect of training on labor supply has been to separate training into two components, general and specific, following the pionieristic 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 therefore bear the cost of specific human capital, while the worker should pay for her general human capital. The traditional view problem is that it is unclear what defines training as either specific or general. Moreover, it does not explain the empirical evidence of employers paying for apparently general training (Acemoglu and Pischke, 1999a; Autor, 2001).[3] Therefore, I propose a framework consistent with the empirical evidence, rather than invoking one model for one result and another for other results, where any form of training is contemporaneously general and specific, but their specificity depends on observable labor market parameters. Specifically, in this framework, the economy is segmented between 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 but also to its competing firm within the same market, yet, these skills are useless for firms in other markets. Putting it differently, training is specific for movement across markets, but general within a market. Therefore, according to the market concentration level, the training will be 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

(2011); Picchio and Van Ours (2013); Mohrenweiser et al. (2019); Dietz and Zwick (2021).

[3]Indeed, the same Becker (1964) suggests that this distinction is useful simplification, and in reality neither form of training is neither completely specific nor completely general. Suggesting as well that the degree of specificity could be affected by the labor market structure.

what the monopsonistic literature expects to be a clear negative effect. One way to at least partially explain such a discrepancy in the theoretical and empirical predictions is to see how employer concentration affects training. By increasing the training investment, workers in more concentrated markets are more productive; thus, ignoring this aspect could lead to underestimating the effect of employer concentration on wages.[4] Moreover, as training becomes more specific as concentration increases, implying lower poaching threats, employers will 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 increases by 2 percent and reduces the return of training investment in terms of increasing worker productivity by 1 percent. 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 investments are likelier to invest 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

[4] As training, other potential channel could be affected by employer concentration, for example; R&D, skill demand, recruitment and hiring procedure. All these other potential channels are left for future research.

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, suggesting so that the surprisingly small negative effects of employer concentration could be a lower bound and the actual markdown in principle should 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 where the training specificity changes according to the labor market structure. 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 1.2 illlustrates the conceptual framework. Section 3.4 describes the data. Section 3.5 presents the empirical specifications and the identification strategy. Section 3.6 shows the main results with robustness checks. Finally, Section 1.6 concludes.

1.2 Model

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.

1.2.1 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.[5] 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 define it just as 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

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

by human capital specificity.[6] 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 the number of skills taught to her employees, a employer increases the probability that they move to another competing firm in the same market.

1.2.2 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.[7] 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}.

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

[7] 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.

As a 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:

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

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

where the aggregate disutilities of labor supply are given by,

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

$$\overline{N}_j := \left[\sum_{i=1}^{M_j} \bar{n}_{ij}^{\frac{\eta+1}{\eta}}\right]^{\frac{\eta}{\eta+1}} G(T_j)^{-1} \quad , \quad \eta > 0 \quad \text{and} \quad G(T_j) > 0$$

$$\bar{n}_{ij} := n_{ij}\,g(t_{ij}) \quad , \quad g(t_{ij}) > 0$$

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 η or θ tends 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., $\eta > \theta$.[8]

[8]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

With respect to employer provided training, t_{ij} describes the amount of training provided by the employer i in market j; and T_j is the average amount of on-the-job training offered in market j. $g()$ 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.[9]

As notation, the bar denotes indexes, which are not directly observable variables. For example, $\overline{n}_{ij}$ 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 by the following inverse labor supply curve:

$$w_{ij} = n_{ij}^{\frac{1}{\eta}} N_j^{\frac{1}{\theta}-\frac{1}{\eta}} \mathbf{N}^{\frac{1}{\psi}-\frac{1}{\theta}} g(t_{ij})^{\frac{1+\eta}{\eta}} G(T_j)^{-\frac{1+\theta}{\theta}} \tag{1.1}$$

Interpretation: The micro-foundation of this representative household problem is that

markets.

[9]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.

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 industries or location. Therefore, training reduces the moving costs in both directions, while is more likely that it will affect only the movement across industries. The extension of the model for capturing these two different channels is left for future research.

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

1.2.3 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

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

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

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

1.2.4 Partial equilibrium

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

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

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 optimal level of training investment will be the one such that $MP_{t_{ij}} = \tau$. However, including the idea that training affects also the labour supply, there could be either under- or over-investment. Specifically, it can be shown that

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

Therefore, for every given quantity of 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-investment in training as the training cost is higher that its marginal productivity:

$$\frac{1+\eta}{\eta} \varepsilon_{gt} < \frac{1+\theta}{\theta} \varepsilon_{Gt} \;\Rightarrow\; MP_{t_{ij}} < \tau$$

Therefore, the more dominant is an employer in a local labor market, the larger is her impact on the market level training component, the larger is her investment in training. Even though the training returns in term of productivity are lower than its costs, she will face this excessive cost in order to increase her labor supply.

Assuming the firm will choose the optimal level of investment given the 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:

$$MPL_{ij} = (1 + \epsilon_{ij})w_{ij} \tag{1.2}$$

where

$$\epsilon_{ij} = \underbrace{(1 - \tilde{s}_{ij})\frac{1}{\eta} + \frac{1}{\theta}\tilde{s}_{ij}}_{\epsilon_{ij}^0} + \left[\frac{1+\eta}{\eta}\varepsilon_{gt} - \frac{1+\theta}{\theta}\varepsilon_{Gt}\right]\varepsilon_{tn} \tag{1.3}$$

where ϵ_{ij} is the inverse labor supply elasticity of wage; MPL_{ij} is the marginal productivity of labor; $\tilde{s}_{ij}$ 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, i.e., how the employment share of a firm impacts her training investment. Finally, ϵ_{ij}^0 is the inverse labor supply elasticity of wage if there are no training component:

$$\epsilon_{ij}^0 = (1 - \tilde{s}_{ij})\frac{1}{\eta} + \frac{1}{\theta}\tilde{s}_{ij} \tag{1.4}$$

First, considering the case without training component ϵ^0, the inverse labor supply depends on the within (η) and across (θ) market substitution elasticities, and the employment-share ($\tilde{s}_{ij}$). 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 markdown. 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 rationale behind is that the larger a firm is, the more expensive it is to hire new workers, due to the upward labor supply curve, but at the same time the higher is the returns it extracts from the 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. On the other hand, relative small firms can more easily poach workers from their competitors, since the movement costs within a market are smaller than across markets.

From equation 1.3, we can observe that ignoring the training factor will lead to underestimate the effect of labor market concentration on the wage markdown $\mu_{ij} = 1 + \epsilon^0_{ij}$. Indeed, the larger is the influence of an individual firm training investment on the market level training investment, the larger will be the downward bias. Indeed, the larger is ε_{Gh} with respect to ε_{gh} the larger is the change in the inverse labor supply elasticity ϵ_{ij} when controlling for the training investment.[12]

Market level aggregation:

To better grasp the relationship between employer concentration and wages markdown, I have to provide some structure to the training sensible labor disutility elasticities ($\varepsilon_{gt}, \varepsilon_{Gt}$). For ease of exposition, consider the following functional forms

$$\varepsilon_{gt} = \alpha t_{ij} \qquad \qquad \varepsilon_{Gt} = \beta \bar{t}_j s_{ij} \tag{1.5}$$

where α and β are two positive coefficients; s_i is the employment share of firm i in market j; and $\bar{t}_j$ is the market average employer-provided training. The idea behind the function forms is that the disutility of working in firm within a market increases with the level of training, i.e. higher training investment increases the poaching threats from within-

[12]Moreover, the smaller is the importance of wages in the choice of a market (θ or $\eta \to 0$), the larger in absolute values is the bias.

market competitors. On the other hand, larger is the firm larger is the probability that employees changing market will moving to that specific firm. Therefore, for given level of average market training, larger is the employment share of a firm, larger is the probability to attracting workers from other markets.

Substituting the elasticities in Equation 1.5 into Equation 1.3 and taking the market average,

$$\bar{\mu}_j = 1 + \sum_i s_{ij}\epsilon_{ij} = a - bHHI_j + c\bar{t_j}HHI_j + d\bar{t_j} \tag{1.6}$$

where $\bar{\mu}_j$ is the market average wage markdown, HHI_j is the employment Herfindahl-Hirschman index ($\sum_i s_{ij}^2$), and latin letters a to d are positive coefficients.[13] Given this functional form, one can see how the effect of employer concentration on the wages markdown change with respect to training. Specifically, without controlling for training, the estimated effect of a change in the HHI is $-b + c\bar{t_j}$, while controlling also for the training, the effect of HHI will be only equal to $-b$. Therefore, the larger is the average market training, the larger will be this gap.

Empirical Predictions:

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

[13] As additional assumptions, I have assumed that ε_{tn} is a constant and approximated $\tilde{s}_{ij}$ to s_{ij}. The results shown arise from convenient assumptions made for a pure illustrative reason, which are clearly stronger than necessary. Indeed, the results persist with less stringent assumptions. The key assumption is that the market training disutility elasticity grows more than the firm training disutility elasticity as the employment share rises, which is a very reasonable assumptions as it is likelier that workers moving from other markets will be likely be employed by larger firms, thus, with larger shares the larger the benefit from an inflow of workers from other markets.

increase the recruitment rate without drastically increasing the wages and without the threat of seeing their employees poached by competitors. As this effect of training on the labor supply becomes prominent, employers recurs to training more as an attractive device, rather than to increase worker productivity. Consequently, at high concentration levels, training produces less return in terms of increase in productivity and wages.

Ultimately, the main predictions on the effect of employer concentration can be summarized as follow: higher concentration (i) reduces wages but (ii) promotes employer-provided training, (iii) it has a positive but decreasing effects on labor productivity, and (iv) controlling for changes in training investments should lead to larger negative estimated effects of concentration on wages.

1.3 Data

To test the empirical predictions obtained in section 1.2, I exploit two main data sources: the Italian Orbis dataset and the *Rilevazione longitudinale su Imprese e Lavoro* (RIL).

1.3.1 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 concentra-

[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).

tion, 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.

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,

$$HHI_{mt} = \sum_{j=1}^{N} \left(\frac{e_{jmt}}{\sum_{k=1}^{N} e_{kmt}} \right)^2 \tag{1.7}$$

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]

[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).

[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.

Table 1.1 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 1.1 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 F.1.8 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 Rario (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 **??**, these three concentration indexes are highly correlated.

1.3.2 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 1.2 report the summary statistics associated with these two samples. Figure 1.2 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 1.3 displays the average training outcomes across 1 digit NACE industries.

1.4 Empirical strategy

The theory in Section 1.2 suggests that employer concentration should have (i) a negative effect on wages, (ii) a positive effect on training, and (iii) an a decreasing returns of training investment in terms of increase in workers' productivity. The empirical approaches to test these predictions are described respectively in Sections 1.4.1, 1.4.2, and 1.4.3.

To account for possible endogeneity, I develop instrument for the HHI index, discussed further in Section 1.4.4

[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.

1.4.1 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:

$$\log(w_{jmt}) = \beta \log(HHI_{mt}) + \alpha X_{jmt} + \text{fixed effects} + \varepsilon_{jmt} \tag{1.8}$$

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.

1.4.2 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:

$$Y_{jmt} = \beta \log(HHI_{mt}) + \alpha X_{jmt} + \text{fixed effects} + \varepsilon_{jmt} \tag{1.9}$$

where subscript j, m, and t indicate as in Equation 1.8 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]

1.4.3 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:

$$log(Y_{mt}) = \beta \log(HHI_{mt}) \times IHS(T_{mt}) + \gamma IHS(T_{mt}) + \alpha X_{mt} + \text{fixed effects} + \varepsilon_{mt} \quad (1.10)$$

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 1.10, the estimated labor productivity elasticity on employer provided training investment reads as follow:

$$Elasticity_{Y,T} := \frac{\partial log(Y_{mt})}{\partial IHS(T_{mt})} = \hat{\gamma} + \hat{\beta} log(HHI_{mt}) \quad (1.11)$$

[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.

In this case, β is estimated instrumenting the interacted term $(\log(HHI_{mt}) \times IHS(T_{mt}))$ with the interaction between $IHS(T_{mt})$ and the instrument of $log(HHI_{mt})$ as described in Section 1.4.4.

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

$$log(W_{mt}) = \beta_1 log(HHI_{mt}) + \alpha X_{mt} + \text{fixed effects} + \varepsilon_{mt} \tag{1.12}$$

$$log(W_{mt}) = \beta_2 log(HHI_{mt}) + \gamma IHS(T_{mt}) + \alpha X_{mt} + \text{fixed effects} + \varepsilon_{mt} \tag{1.13}$$

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 1.4.4. 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.

1.4.4 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.

$$log(HHI^{instr.})_{mt} = \frac{1}{M-1} \sum_{k \neq m} -log\left(\sum_{j} \mathbb{1}(e_{jmt} > 0)\right) \tag{1.14}$$

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 squared national revenues shares in a market.

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:

$$Z^{HHI}_{i,r,t} = log \left\{ \sum_j s^2_{j,i,r,t-1} \left[\frac{(1+\tilde{g}_{j,k(i),-r,t})^2}{(1+\tilde{g}_{i,r,t})^2} - 1 \right] \right\} \tag{1.15}$$

[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.

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[21]; $\tilde{g}_{i,r,t}$ 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.

1.5 Results

This section shows the main results on the effects of employer concentration on wages, subsection 1.5.1, on employer provided training investment, subsection 1.5.2, and on the

[21]Formally, $\tilde{g}_{j,k(i),-r,t} = \sum_{s \neq r} \frac{e_{j,k(i),s,t}}{e_{j,k(i),s,t-1}} - 1$

combined effect on wages and productivity, subsection 1.5.3.

1.5.1 Effects on wages

Following Equations 1.8 and 1.14, I estimate the impact of employer concentration on firm's mean yearly wages. Results are shown in Table 1.3. 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 1.4.4 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.[22] At the same time, the estimates considering employer fixed effects are also drastically larger underlying the importance to control for all time-invariant firm characteristics.

Robustness and sensitivity

To test the sensitivity of the effects on wages to different definitions of local labor market, Table T.1.1 reports the results of the IV specification with employer and year fixed effects, analogous to Column 3 of Table 1.3, with different market specifications. Specifically,

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

Panel A considers NUTS level 2 (Italian "regioni") as the geographical definition as in Table T.1.1, 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 1.4.4 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 1.5 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-Hirshman 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 firms. For all the three different indexes, they are 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 1.6 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 1.4.4. 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 T.1.5 shows the results when controlling for the product market concentration. The results are in line with what reported in Table 1.3, specifically, in the preferred specification with year and employer fixed effects, the effect of employer concentration on wages is even slightly larger.[23]

1.5.2 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 1.9, 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.[24]

Table 1.4 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.[25] 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.[26]

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[23] 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.

[24] 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: $IHS(X) = log(x + \sqrt{x^2 + 1})$

[25] The first stage is reported in Table T.1.3.

[26] 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 1.2.

In Table 1.5, 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 1.4 but becomes slightly smaller in magnitude.

Moving on the intensive margin, Tables 1.6 and 1.7 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 1.7, 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.[27]

Finally, Tables 1.8 and 1.9 replicate the analysis in Tables 1.6 and 1.7, where the dependent variable is the total amount of Euro invested in training by the employer. Table 1.8 accounts for the entire sample. Table 1.9 focuses on the panel sample. The results are in line with those on the investment per workers, yet slightly less significant.

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 1.5.1, Figure 1.7 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

[27] 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 B.2.

effects become even larger with the inclusion of market level controls in all the different specifications and across the different concentration indexes.

Figure 1.8 compares the TSLS results using the baseline Hausmann instrument (eq.1.14) and the Bartik instrument (eq.1.15) on the three training outcomes. The Bartik instrument obtains even larger positive effects of employer concentration on employer provided training.[28]

Finally, the results are also robust to the control for product market concentration, Tables T.1.6, T.1.7, and T.1.8 report the results with respect to employer-provided training probability, training investment per worker, and total training investment, respectively.

1.5.3 Combined Effects on Productivity and Wages

To explore the impact of employer concentration and training investments on workers productivity, as depicted in Section 1.4.3.

Table 1.10 estimates Equation 1.10, 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 1.14 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[29], the elasticity of labor productivity to market average training

[28]The first stage using the IV-B is reported in Table T.1.4.

[29]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.

is around 0.16. However, this elasticity decreases at rise of the HHI, considering an inter-quartile range change in log HHI from 1.2, i.e. moving from 4 to 6, the elasticity of labor productivity to training goes from 0.07 to 0.02.[30] Figure 1.9 illustrates this decreasing elasticity with respect to employer concentration.

Table 1.11 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 1.12 and 1.13.

Table 1.12 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

[30]Interestingly, the coefficients of HHI are positive and significant. A possible justification can be extracted from the model in Section 1.2. As firms are identical except for their productivity, for generate high level of concentration, there should be a few very productive firms.

by around 1.6 log points.[31]

Overall, even if not conclusive, these findings support the empirical predictions of the model in Section 1.2. 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.

1.6 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 10 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 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

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

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.

A List of Tables and Figures

A.1 List of Tables

Table 1.1: 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×10k	2,691,810	441	886	63	161	420	1,001
log(HHI×10k)	2,691,810	5.12	1.36	4.14	5.08	6.04	6.91
value added	2,691,810	41,361	106,974	7,821	28,988	50,034	79,558
value added per worker	2,691,810	462,021	1,118,816	18,609	111,912	371,824	1,045,751
value added over wagebill	2,691,810	2.35	11.7	1.08	1.67	2.26	3.61
				Market level			
HHI×10k	29,911	3,057	3,214	573	1,700	4,560	10,000
log(HHI×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 1.2: Summary statistics: RIL Cross-section dataset

	N	mean	sd	p25	median	p75	p90
PANEL A: *RIL Cross-section dataset*							
Training dummy	48,046	.28	.45	0	0	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	.33	.47	0	0	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 1.3: 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 1.4.4. 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 1.4: 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 1.4.4. "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 1.5: 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 1.4.4. "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 1.6: 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 1.4.4. "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 1.7: 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 1.4.4. "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 1.8: 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 1.4.4. "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 1.9: 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 1.4.4. "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 1.10: 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 1.4.4, 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 1.11: 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 1.4.4, 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.

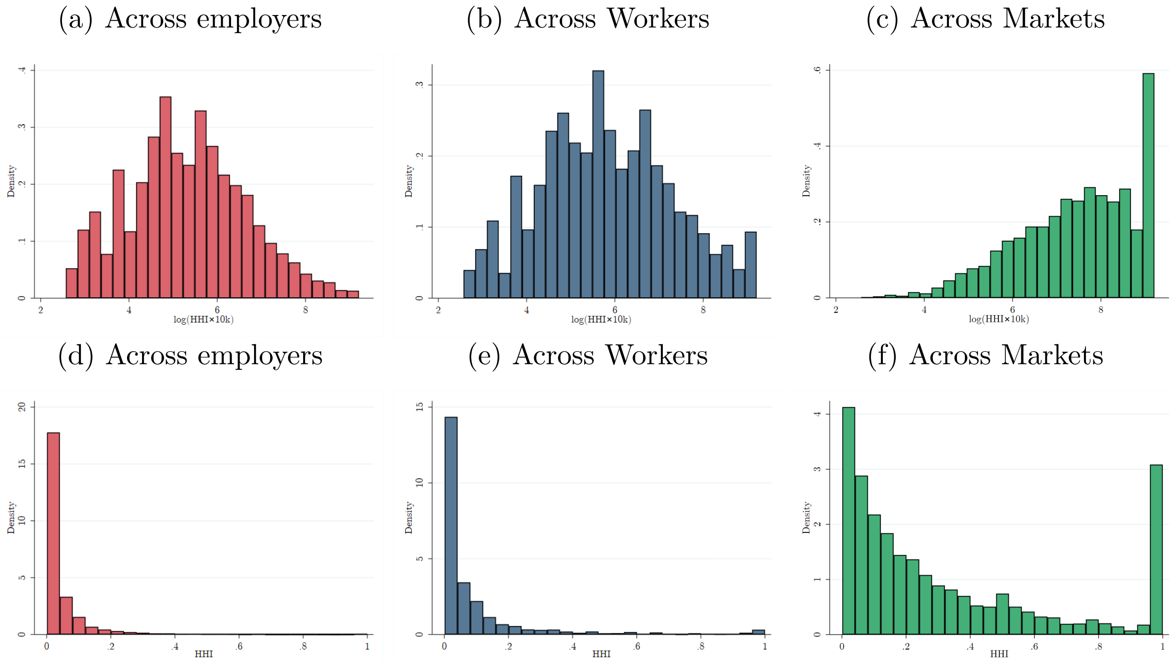
Table 1.12: Effects on labor productivity: market level IHS training prob.

	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 1.4.4, 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.

A.2 List of Figures

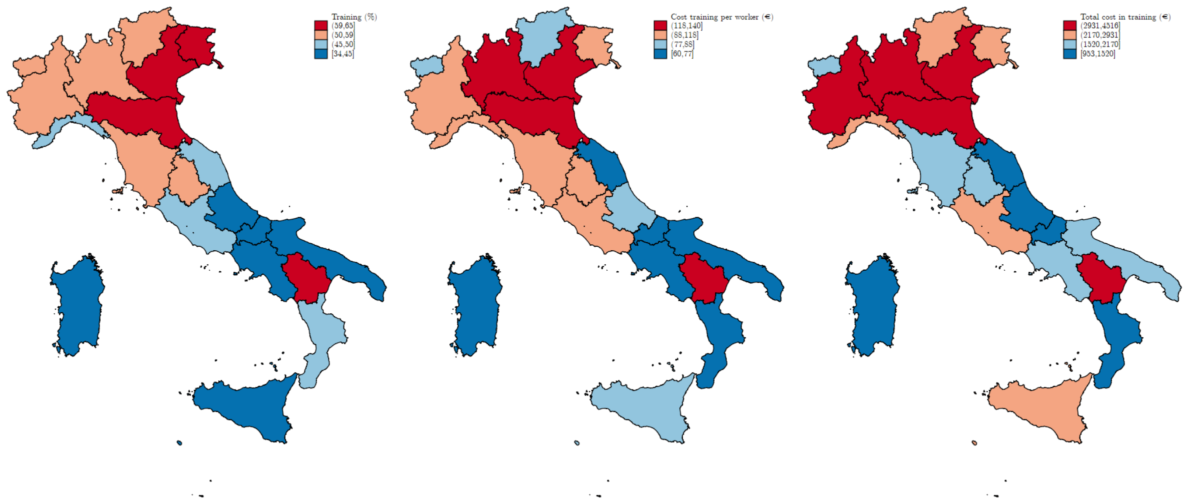
Figure 1.1: Histograms of employer HHI across employers, workers, and markets



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 1.2: Maps employer training investments across NUTS level 2 region

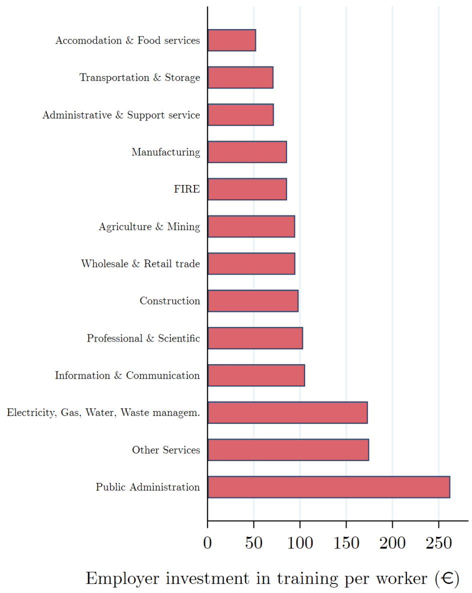
(a) Training prob. (b) Investment per worker (c) Total investment



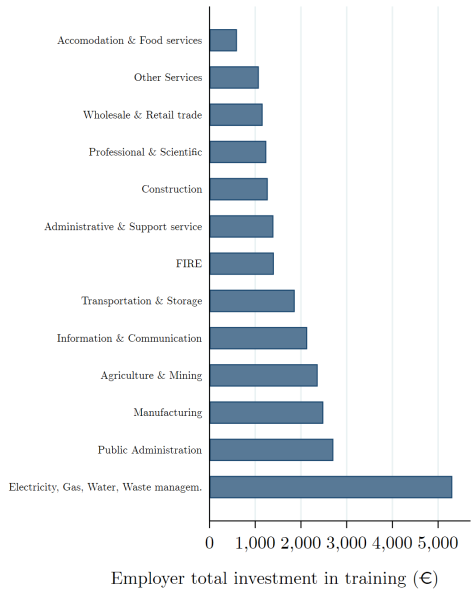
Note: Maps of training investment across NUTS level 2 region. Panel (a) illustrated the average probability that an employer provides any form of training to her workforce; Panel (b) the average yearly amount of euro investment per worker; Panel (c) the total amount invested by an employer in training. 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 1.3: Employer-provided training investment across industry sectors

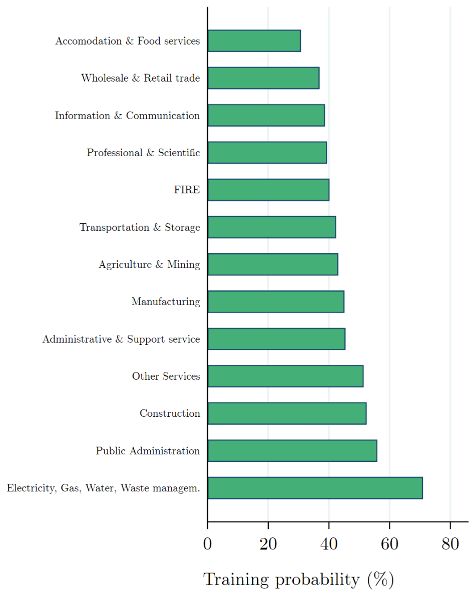
(a) Investment per worker



(b) Total investment

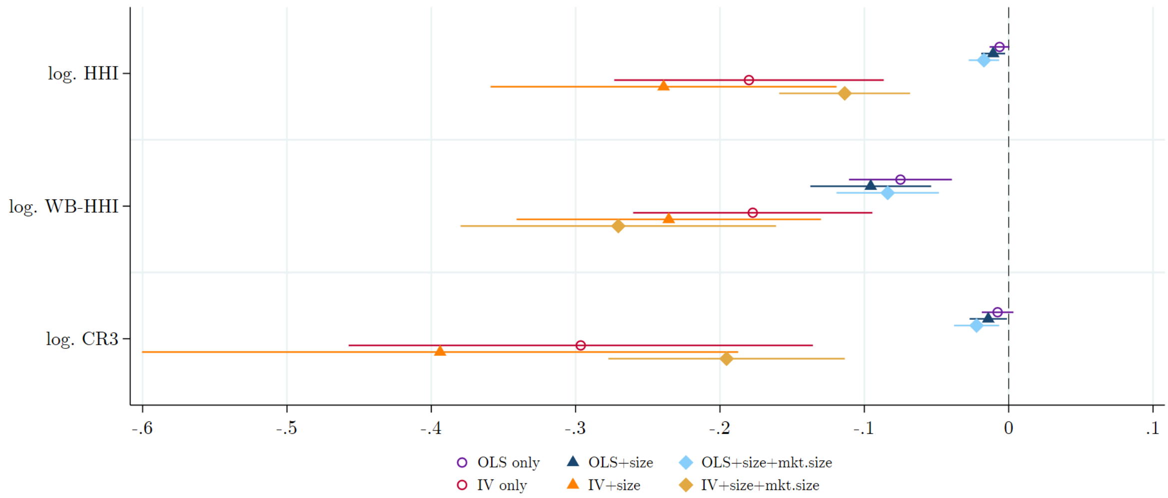


(c) Training prob.



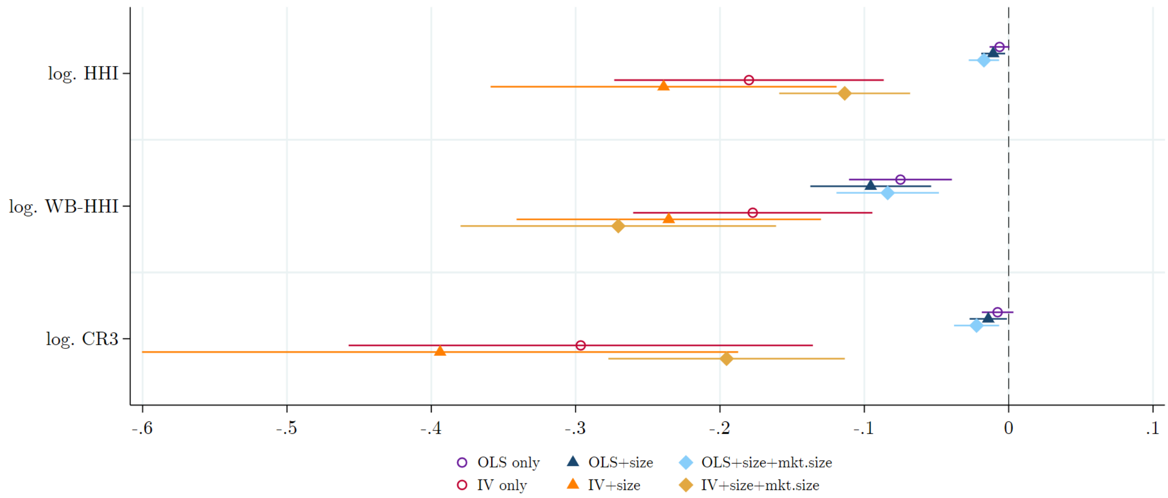
Panel (a) illustrated the average yearly amount of euro investment per worker; Panel (b) the total amount invested by an employer in training; Panel (c) the average probability that an employer provides any form of training to her workforce. All the measures are aggregated at the industry sector level 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 & Scentific"=M; "Administrative & Support service"=N; "Public Administration"=(O,P,Q); "Other Services"=(R,S,T,U).

Figure 1.4: Wage elasticity of employer concentration: Sensitivity to concentration indexes



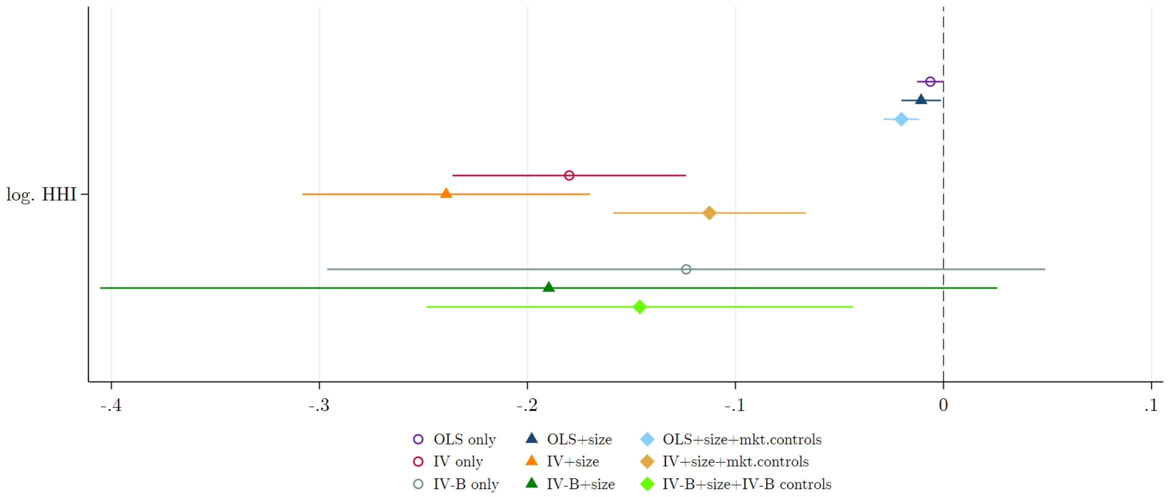
Note: The figure plots both the OLS and TSLS estimated wage elasticity of employer concentration and their 95% confidence intervals considering different concentration measures, and different set of controls. The "size" control measures the number of workers employed by each employer. The "market size" 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 1.5: 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 **??**

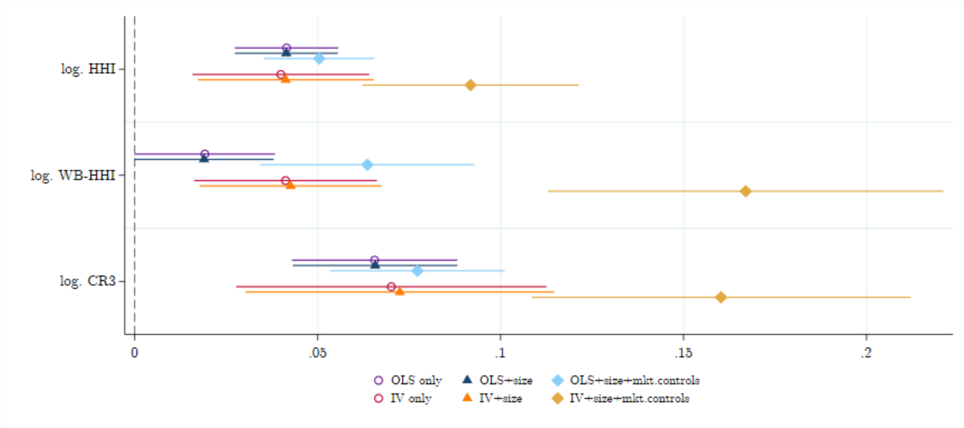
Figure 1.6: Wage elasticity of employer concentration: Robustness alternative IV



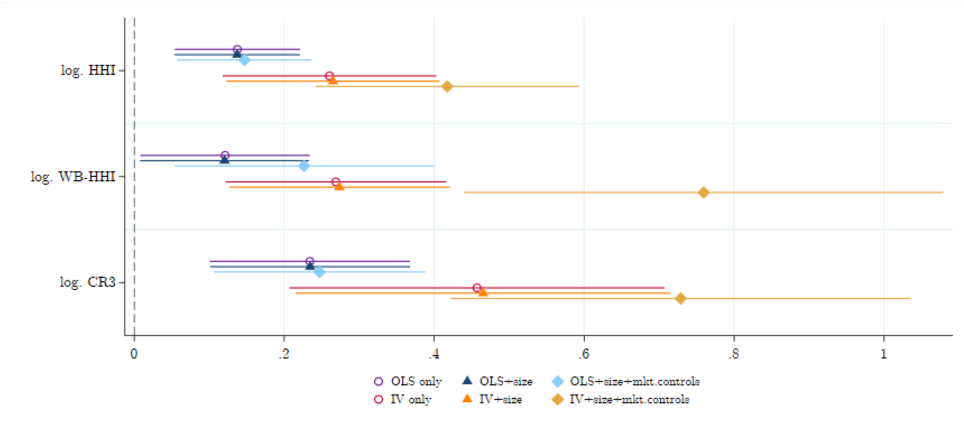
Note: The figure plots both the OLS and TSLS estimated wage elasticity of employer concentration and their 95% confidence intervals considering different the standard instrument as in Equation 1.14, as well as the "Bartik instrument" (IV-B) of Equation 1.15. The "size" control measures the number of 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 1.4.4. 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 1.7: Effects on Employer Provided Training: Sensitivity to concentration indexes

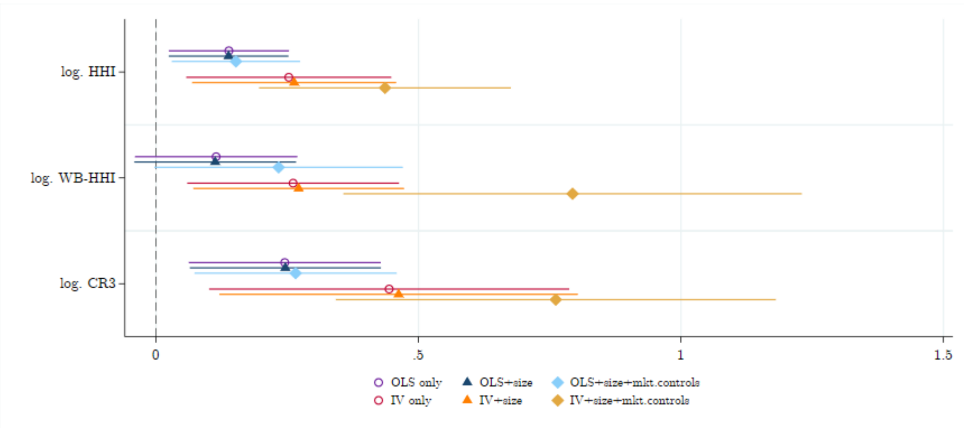
(a) Training Probability



(b) IHS Training Investment Cost per Worker



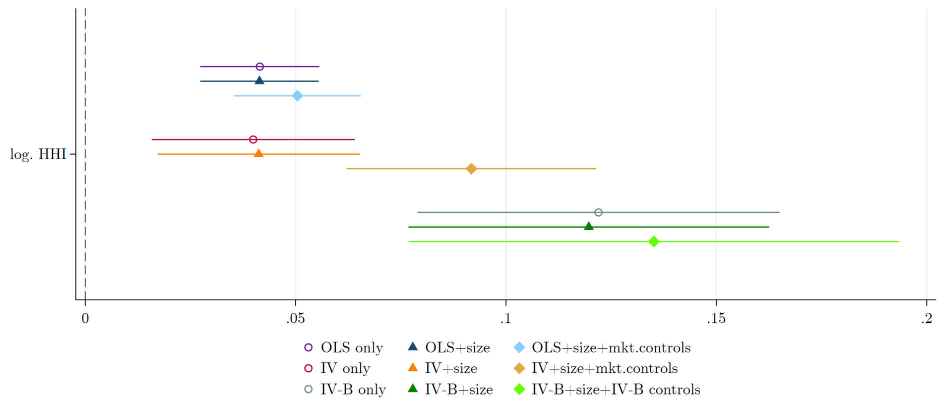
(c) IHS Total Training Investment Cost



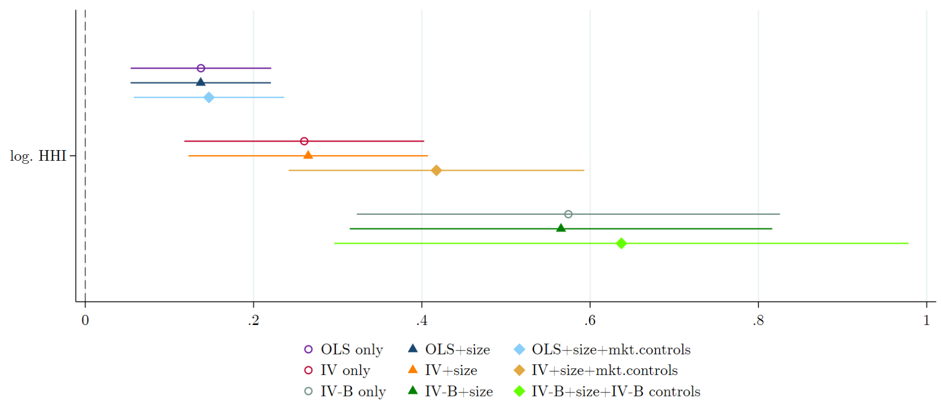
Note: The figure plots the OLS and TSLS estimated effects on (a) the probability an employer provides training, (b) the IHS of the employer investment in training per worker, and (c) the IHS employer total investment in training. The "size" control measures the number of workers employed by each employer. 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 1.8: Effects on Employer Provided Training: Robustness alternative IV

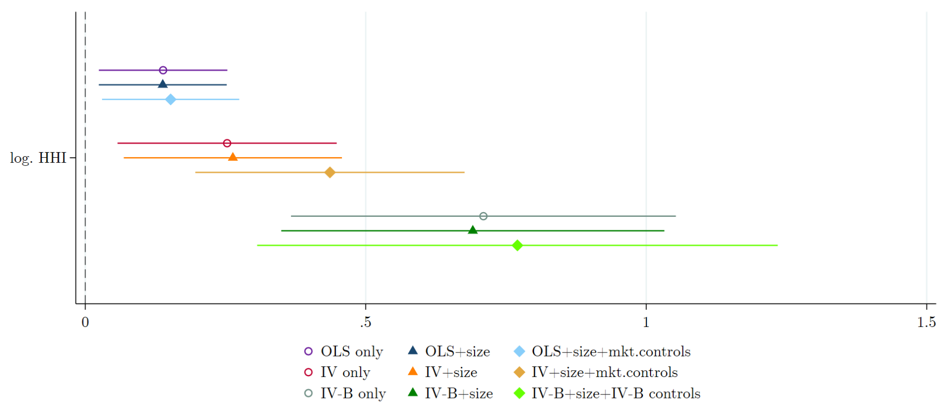
(a) Training Probability



(b) IHS Training Investment Cost per Worker



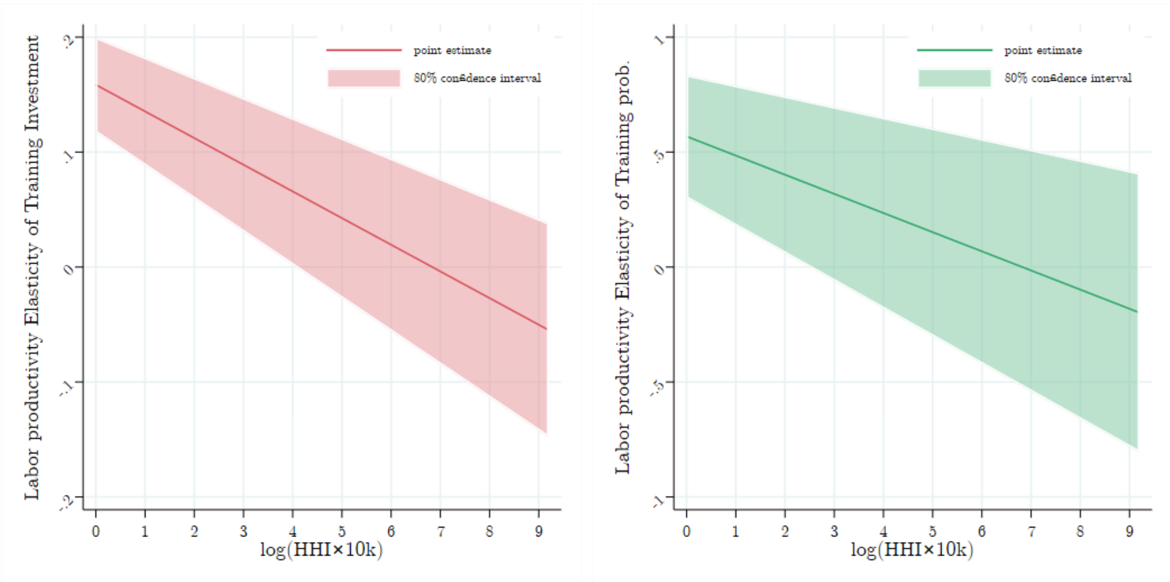
(c) IHS Total Training Investment Cost



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 1.14, as well as the "Bartik instrument" (IV-B) of Equation 1.15. 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 1.4.4. All the specification controls for year and employer fixed effects.

Figure 1.9: 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 1.11 using the estimates from Tables 1.10 and 1.11, Column (4).

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B Math Appendix

B.1 Conceptual Framework: Mathematical derivations

To derive the labor supply of Equation 1.1, 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 $\mathbf{C}$ and $\mathbf{N}$ 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:

$$\mathbf{N}^{\frac{1}{\varphi}} = \mathbf{W} \tag{1.16}$$

The problem at the second stage reads as

$$\mathbf{N} := \min_{\overline{N}_j} \left\{ \int_0^1 \overline{N}_j^{\frac{\theta+1}{\theta}} \, \mathrm{d}j \right\}^{\frac{\theta}{\theta+1}} \tag{1.17}$$

s.t.

$$\int_0^1 W_j N_j \,\mathrm{d}j \geq \mathbf{C} \tag{1.18}$$

$$\overline{N}_j := N_j G(T)^{-1} \tag{1.19}$$

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 $\mathbf{W}$ 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

$$\left[\int_0^1 \overline{N}_j^{\frac{\theta+1}{\theta}} dj\right]^{-\frac{1}{\theta+1}} \overline{N}_j^{\frac{1}{\theta}} = \lambda \overline{W}_j \tag{1.20}$$

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 $\int \overline{N}_j^{\frac{\theta+1}{\theta}} dj = \mathbf{N}^{\frac{\theta+1}{\theta}}$,

$$\mathbf{N}^{\frac{\theta+1}{\theta}-\frac{1}{\theta}} \int_0^1 \overline{N}_j^{\frac{1}{\theta}} dj = \lambda \int_0^1 \overline{W}_j \overline{N}_j \tag{1.21}$$

Using the definition of $\mathbf{W}$

$$\mathbf{W}^{-1} = \lambda \tag{1.22}$$

Substituting 1.22 into 1.20,

$$\overline{N}_j = \left(\frac{\overline{W}_j}{\mathbf{W}}\right)^{\theta} \mathbf{N} \tag{1.23}$$

To derive the function of the wage index $\mathbf{W}$, multiply by $\overline{W}_j$ both side of Equation 1.23 and integrate

$$\int_0^1 \overline{W}_j \overline{N}_j = \mathbf{W}^{-\theta}\mathbf{N} \int_0^1 \overline{W}_j^{1+\theta} dj \tag{1.24}$$

$$\mathbf{W} = \left[\int_0^1 \overline{W}_j^{1+\theta}\, dj\right]^{\frac{1}{1+\theta}} \tag{1.25}$$

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

$$G(T)^{-1} \left[\sum_i \overline{n}_{ij}^{\frac{\eta+1}{\eta}}\right]^{-\frac{1}{1+\eta}} \overline{n}_{ij}^{\frac{1}{\eta}} = \lambda \overline{w}_{ij} \tag{1.26}$$

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

$$\overline{N}_j = \lambda \overline{W}_j \overline{N}_j \tag{1.27}$$

Substituting 1.26 into 1.27, and re-arranging

$$\overline{n}_{ij} = \left(\frac{\overline{w}_{ij}}{\overline{W}_j}\right)^{\eta} \overline{N}_j \, G(T)^{\eta+1} \tag{1.28}$$

As before, we can derive $\overline{W}_j$, by multiplying 1.28 with $\overline{w}_{ij}$ and sum over i

$$\overline{W}_j = \left[\sum_i \overline{w}_{ij}^{1+\eta}\right]^{\frac{1}{1+\eta}} G(T) \tag{1.29}$$

To conclude, by combining Equations 1.16, 1.23, 1.28:

$$\overline{n}_{ij} = \left(\frac{\overline{w}_{ij}}{\overline{W}_j}\right)^{\eta} \left(\frac{\overline{W}_j}{\mathbf{W}}\right)^{\theta} \mathbf{W}^{\varphi} G(T)^{\eta+1} \tag{1.30}$$

which is equivalent to

$$n_{ij} = \left(\frac{w_{ij}}{W_j}\right)^{\eta} \left(\frac{W_j}{\mathbf{W}}\right)^{\theta} \mathbf{W}^{\varphi} G(T)^{1+\theta} g(t)^{-1-\eta} \tag{1.31}$$

To obtain the inverse labor supply (as in Equation 1.1), invert the Equations 1.16, 1.23, 1.28; to express wages as function of labor and then combined.

B.2 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

$$\tilde{y} = \alpha + \beta log(x) + \epsilon \tag{1.32}$$

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

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 1.32 and a mean value of y of 123 (that is the mean employer provided investment in training per worker, see Table 1.2), 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:

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

C Extra Tables and Figures

C.1 Extra Tables

Table T.1.1: 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 1.14. 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 T.1.2: 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 1.14, while "IV-B" to the instrument described in Equations 1.15. "Exposure control", "predicted employment growth", and "actual employment growth" are the additional controls for the Bartik instrument (IV-B), as described in Section 1.4.4. Robust standard errors, in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table T.1.3: 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 1.14. Robust standard errors, in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table T.1.4: 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 1.15. "Exposure control", "predicted employment growth", and "actual employment growth" are the additional controls for the Bartik instrument (IV-B), as described in Section 1.4.4. Robust standard errors, in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table T.1.5: 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 1.4.4. 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 T.1.6: 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 1.4.4. "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 T.1.7: 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 1.4.4. "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 T.1.8: Robustness for product concentration: IHS total training investment

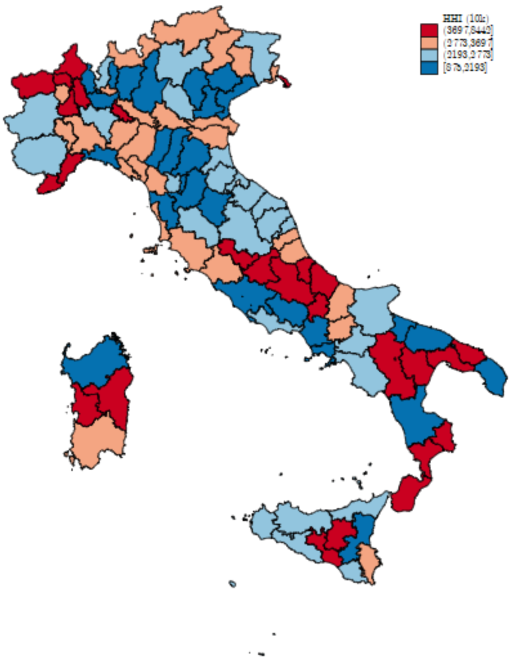
	OLS		IV	
	(1)	(2)	(3)	(4)
log. employment HHI	0.1098*	0.1162*	0.2266**	0.2507**
	(0.0616)	(0.0613)	(0.1132)	(0.1127)
log. product HHI	0.0483	0.0367	0.0282	0.0134
	(0.0327)	(0.0326)	(0.0364)	(0.0363)
log. employees		0.9792***		0.9819***
		(0.1005)		(0.1006)
Year	✓	✓	✓	✓
Employer	✓	✓	✓	✓
MDV	4.21	4.21	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 1.4.4. "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.

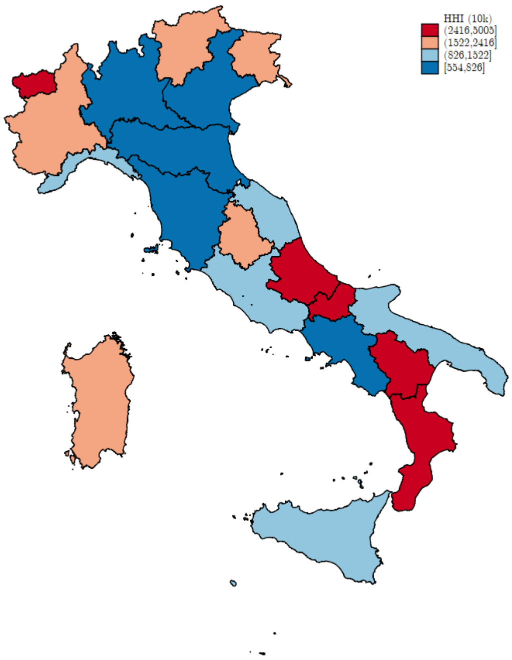
C.2 Extra Figures

Figure F.1.8: Employer concentration across different local labor market definitions

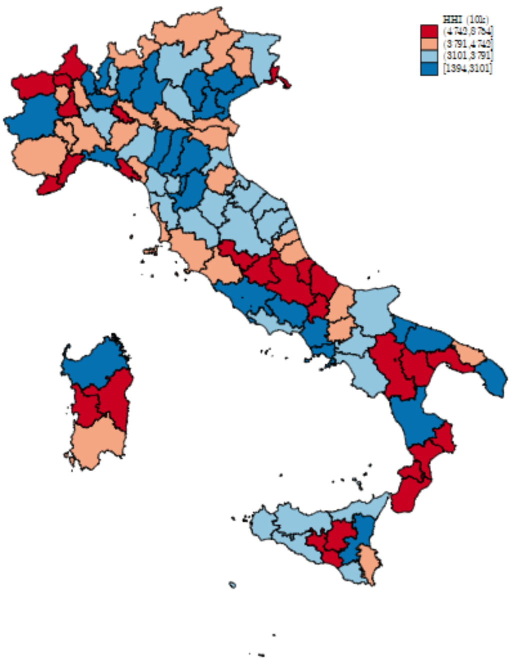
(a) LLM = NUTS 3 × NACE 3



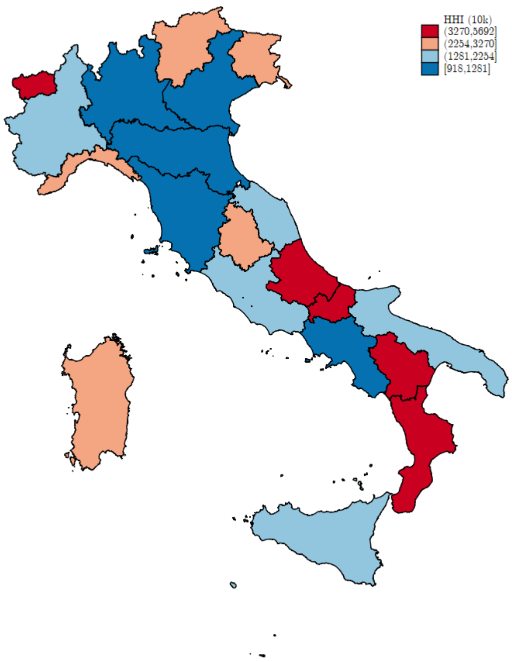
(b) LLM = NUTS 2 × NACE 3



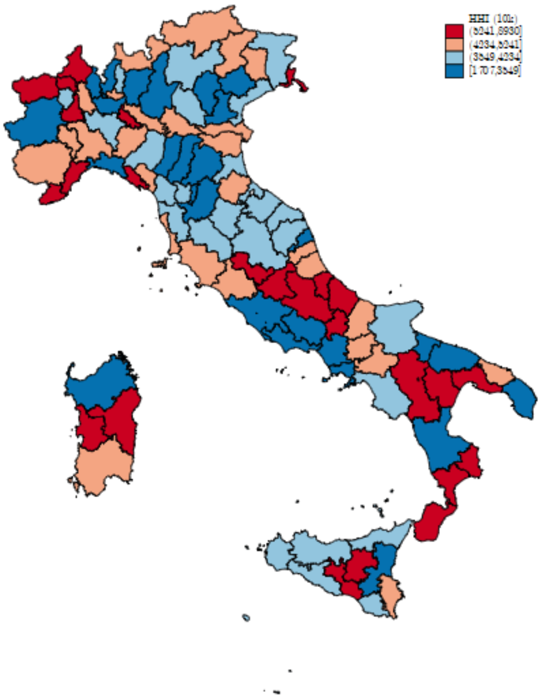
(c) LLM = NUTS 3 × NACE 4



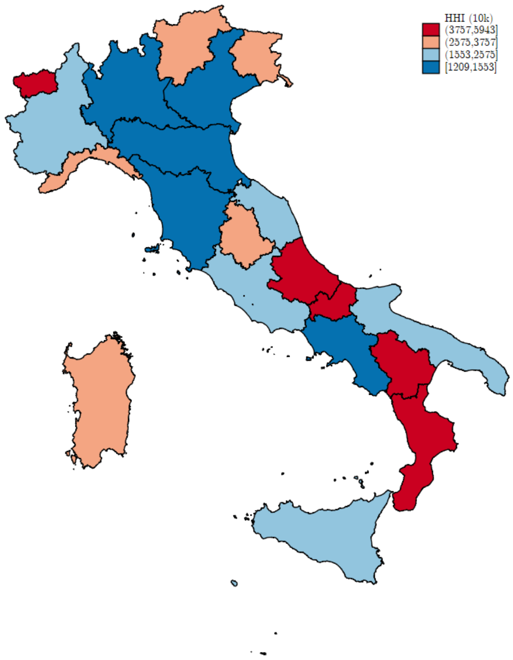
(d) LLM = NUTS 2 × NACE 4



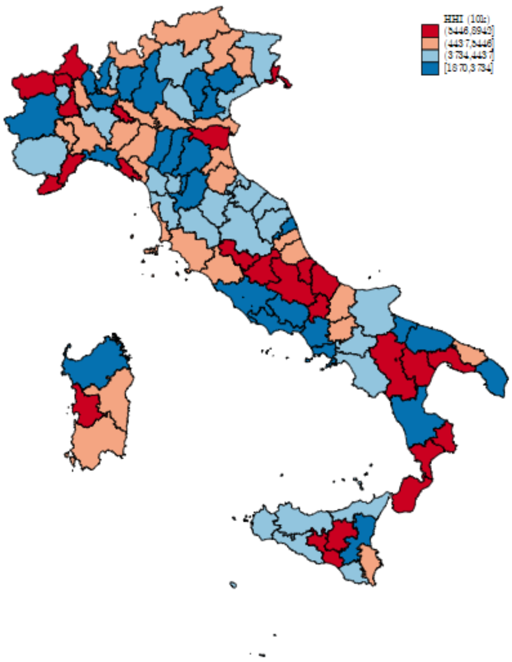
(e) LLM = NUTS 3 × NACE 5



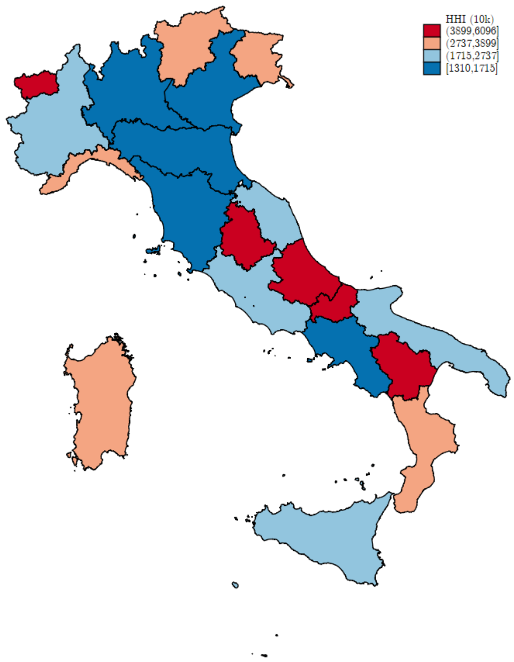
(f) LLM = NUTS 2 × NACE 5



(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.

Chapter 2

On-the-job training and labor market competition

This chapter is based on joint work with Abi Adams-Prassl and Thomas Le Barbanchon

2.1 Introduction

On-the-job training is crucial in many industrialized countries. In light of an aging population and rapid technological changes, promoting lifelong training is a key challenge for policymakers to maintain an efficient and productive workforce (U.S. Council of Economic Advisers, 2018; EU Council, 2019). Yet, the government has limited influence on the on-the-job training provision, relying primarily on private employers (Carnevale et al., 2015). Therefore, it is essential to explore the determinants that stimulate employer-provided training, especially in the aftermath of the Covid-19 pandemic, which 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). Despite its evident relevance, little is known about the mechanisms that drive employer-provided training.

In an influential paper, Acemoglu and Pischke (1998) suggests that labor market power can stimulate employers to provide training. By exerting monopsony power, i.e., by setting wages below the workers' marginal productivity, employers have an incentive to increase labor productivity. However, this relationship between labor market power and training relies on the strong assumption that the labor supply elasticity does not change after training. As pointed out by Manning (2003), it is entirely plausible for trained workers to have better outside options than untrained ones, leading to a more extensive bargaining power from the trained workers and thus a lower incentive for monopsonistic employers to provide on-the-job training. By virtue of recent evidence documenting strong labor market power, the question of whether monopsony power can affect on-the-job training provision experience a recent revival (U.S. Council of Economic Advisers, 2016). Yet, the question is still unsettled, and the empirical evidence is scant. A key reason for this is the lack of high-quality data on training provision and of an identification strategy to deal with the measurement of labor market competition.

This paper studies the effect of labor market competition on employer-provided training and sheds light on the mechanisms behind this effect. We exploit the job vacancy data from Burning Glass Technologies (BGT) database to construct training and labor market competition measures. Relying on a Bartik-style instrument, we find that labor market competition favors on-the-job training provisions and is associated with reducing the probability of a vacancy posting wage information.

Traditionally, training information is collected using questionnaire-based surveys. Still, these have some crucial drawbacks as they are costly, have time lags, lack extensive coverage at the geographical level, prevent conducting across labor market analysis, and require the truthful participation of workers or firms. In contrast, nearly every firm has online job vacancies, which has been shown to contain useful information (Adams-Prassl et al., 2020; Ash et al., 2020). Therefore, this paper provides a new measure of employer-provided training based on job vacancies in the U.S. We use a sample of manually tagged vacancies to train a supervised machine learning (ML) model that can capture content on the employer-training provision. Comparing our ML indicator with survey-based data shows that our training indicator leads to plausible results. We find that around 20 percent of job vacancies offer on-the-job training, with an upward trend over the last decade.

Consistent with classical and recent literature, we quantify labor market competition with a measure of employer concentration.[1] We follow Azar et al. (2020b) in measuring employer concentration with a Herfindahl-Hirschman Index (HHI) measured at a combination between a metropolitan statistical area (MSA), 6-digit Standard Occupation Classification code (SOC), and a year. We further show that employer concentration is correlated with lower job transitions, which is consistent with a theory of oligopsonistic labor markets in which employers compete for workers a la Cournot. We use a Bartik-style instrumental variable approach to deal with the endogeneity of the labor market concentration measure. We instrument labor market concentration changes in a local labor market with the predicted variations in the number of vacancies constructed from the variations at the national level of firms posting behavior, excluding that specific local labor market (Schubert et al., 2020). Under the key assumption that a firm's decision to post vacancy at the country level is not affected by local labor market specificities, this approach provides shocks independent of market unobservable characteristics that can affect on-the-job training decisions.

Next, we investigate how labor market competition affects what an employer posts in a job vacancy. A related concern is that labor market power could affect employers' decision to post wage information. Policymakers have called for employers to disclose

[1]For the classical motivation of employer concentration as a source of monopsony power, as well as for the other potential sources of monopsony power, see (Robinson, 1969; Boal and Ransom, 1997; Manning, 2003); among the most recent papers modeling the relationship between employer concentration and monopsony power, see (Berger et al., 2022; Jarosch et al., 2019).

wage information on job listings, as the lack of pay transparency has been a source of gender wage discrimination.[2] Therefore, understanding what influence the decision of an employer to disclose wage information on job listings is of great importance. We showed that, indeed higher level of concentration leads to lower wage posting. We also provide evidence that employer concentration reduces the requirements of education and experience.

The main findings of the paper can be summarized as follows. First, we find a positive and statistically significant effect of employer concentration on on-the-job training offers. Going from the 25 percentile of the HHI distribution to the 75 percentile is associated with an increase of around 5 percent. Then, we find a negative and statistically significant effect on the probability of posting wages. The same interquartile movement is related to a decrease in the probability of a vacancy posting wage information of 10 percent. We further observed a reduction in the education demanded by around 8 percent and experience by about 3 percent.

Related Literature: This paper builds and extends on different strands of the literature. First, we contribute multiple ways to the scarce literature on the effect of labor market competition on employer-provided training. This paper is the first to develop a machine learning model to extract training information from job vacancy text. Consequently, developing a cost-effective way to measure employer-provided training, which can be quickly updated and covers the near-universe of job vacancies – thus, not having the usual disadvantages of being survey-based. Contrary to most, this paper is one of the few to examine the role of employer concentration and to address the endogeneity of employer concentration through an instrumental variable approach, as well as the first to

[2] Starting from 2021, many jurisdictions are introducing regulations to require wage disclosure in job postings. For example, from January 1, 2023, the State of Washington is the third U.S. jurisdiction (and counting) to introduce this regulation (Washington State, 2022), following Colorado and New York City. It is worth noting that these legislatures do not affect our results, as they are all after our analysis period, which ends in 2019. A similar policy has also been recently discussed in the European Parliament (E.U. Parliament, 2021).

investigate the U.S. market. Harhoff and Kane (1997), Brunello and Gambarotto (2007), and Muehlemann and Wolter (2011) observed a positive correlation between the number of firms in a market and employer-provided training provisions in Germany, the U.K., and Switzerland, respectively. However, neither of those papers addresses the endogeneity problem.[3] Second, we 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. The paper is also close to the literature on using text analysis to extract information from job vacancy text (Deming and Kahn, 2018; Adams-Prassl et al., 2020; Ash et al., 2020) and the literature on vacancy data and wages (Brenčič, 2012; Kuhn and Shen, 2013; Marinescu and Wolthoff, 2020; Le Barbanchon et al., 2021).

The paper proceeds as follows. We describe the data in Section 2.2 and provide some descriptive statistics in Section 2.3. We illustrate the conceptual framework in Section 2.4. We introduce our empirical strategy in Section 2.5 and describe the results in Section 2.6. We explore additional effects in Section 2.7 and we conclude in Section 2.8.

[3] Other related papers are Starr (2019), which observes that workers in U.S. States with more restricted use of non-competing agreements receive less training. Rzepka and Tamm (2016) observed that employer concentration is correlated with larger employer-provided training in Germany, yet they do not address the endogeneity issue besides the use of fixed effects. Finally, Marcato (2021) showed that employer concentration positively affects employers' investment in training in Italy, using a similar instrumental variable approach. Other related papers are (Mohrenweiser et al., 2019; Méndez, 2019; Arellano-Bover, 2020; Bratti et al., 2021).

2.2 Data

To make progress, we turn to information on training contained in job vacancies. Our primary data source is a database of online job ads provided by Burning Glass Technologies (BGT). By scraping more than $40,000$ online job boards and company websites, BGT provides job postings data covering the near-universe of occupation, industries, and geographic areas in the U.S. Comparing BGT data to the Job Opening and Labor Force Turnover Survey (JOLTS), Hershbein and Kahn (2018), Deming and Kahn (2018) and Berkes et al. (2018) observed that BGT provides a good coverage of the job openings in the U.S.[4]

Besides the vast coverage and the rich information, a clear advantage of the BGT data is that it provides the text of each job post. This allows us to predict through a machine learning method whether a vacancy offers on-the-job training and to investigate how on-the-job training is impacted by the level of competition faced by employer in her local labor market.

2.2.1 Measuring training in job vacancies

Our goal is to take the information in the job vacancies text and predict the probability that a given vacancy offers on-the-job training. To this end, we take a supervised machine learning approach that relies on manual annotations similar in spirit to Adams-Prassl et al. (2020). The method proceeds as follows:

1. Manually tag a set of job vacancies if they are explicitly offering on-the-job training

2. Define the vocabulary and represents each job vacancy in a matrix format

[4]Recently, the same data source has been widely used in academic research (Blair and Deming, 2020; Forsythe et al., 2020; Schubert et al., 2020; Azar et al., 2020b; Burke et al., 2020; Modestino et al., 2020; Clemens et al., 2021; Kuhn et al., 2018).

3. Train a machine learning model to classify training offers based on the vacancy text;

4. Apply the machine learning model to all job vacancies for use in the subsequent analysis.

Compared to a word search approach, the machine learning approach allows us to predict better the actual disclosure of training offerings in the vacancy text. Indeed, searching for keywords like "training" or "paid training" on the one hand will neglect all those vacancies that will offer training using different expressions such as "we will train you" or "we will provide you paid in-class courses to acquire the required skills". On the other hand, the word search approach will incorrectly label as offering training vacancies, which, for example, requires the newly hired to train customers. Figure F.2.2 compares the percentage of false positives and negatives of the machine learning and word search approaches. Appendix D.1 reports a few examples of false positives and negatives from the word search approach.

Manual tagging

This section describes our manual tagging procedure. We provide a detailed guideline to twelve research assistants, who inspect the text of around 6,000 job vacancies. They manually annotate if a job vacancy offered training and additional label when training was not an employee benefit but a task the employee has to perform; further information is in Appendix D.1.

We do not distinguish between general and specific training, but we consider training as any program that will help new hires acquire new competencies or skills. As the differentiation between the two types is difficult to correctly implement, especially given that the information on the training content is scarcely reported in the job vacancies text. Some examples are: "Paid training", "new employee training", "tuition reimbursement", "continuous professional development", "practice-paid continuing education"; for more information see Appendix D.1.

Before getting to the modeling, we build a vocabulary from the set of annotated vacancies. Next, we tune the vocabulary by filtering out stop words (e.g., and, the, it). Stop words have limited lexical content, and their presence adds a lot of noise and little signal to help us identify when a job vacancy is offering training. We finally break down the vocabulary into countable features. Each vacancy text is represented as a frequency distribution over a vocabulary of words, bigrams, and trigrams (two and three words phrases). The vocabulary is filtered to the 5000 most frequent phrases.

Machine learning model

This section describes how we train the model to predict whether a vacancy offers training. We use a logistic prediction model using as regressors the aforementioned matrix of 5,000 phrases. To select the hyper-parameters, we use five-fold cross-validation in the training set.

Table 2.1 reports the relevant test-set evaluation metrics. Accuracy is the proportion of out-of-sample observation for which the machine-predicted model correctly predict the true label. Recall is the proportion of correct predicted training within the set of vacancies actually offering training (TP/(TP+FN)). Precision instead is the percentage of correct training predictions relative to total number of training predictions (TP/(TP+FP)). Therefore, while precision penalizes false positives, recall penalizes false negatives. F1 is the weighted harmonic mean of precision and recall, thus it penalizes equally false negatives and positives. Finally, another standard metric in binary classification is the AUC-ROC (Area Under the Receiver Operating Characteristics), which takes values between 0 and 1 and tells how much the model is capable of distinguishing between classes. It can be interpreted as the probability that a randomly sampled vacancy offering training is ranked more highly by predicted probability than a randomly selected vacancy not offering training.[5] Performance are quite good with test-set accuracy = 0.80, AUC-ROC = 0.86, and F1 = 0.71.[6] The model is somewhat conservative in identifying training offers (recall = 0.67), but with good precision (0.76). Figure F.2.2 shows the comparison in term of false positives and false negatives using our machine learning model instead of a more straightforward word search approach. Comparing the metrics, the word search approach largely underperforms the machine learning approach with a F1 score of 0.616, with a good recall of 0.806 but a poor precision of around 0.498.

In addition to the classification metrics, Figure F.2.2 shows how the logistic regression is well-calibrated. Specifically, the figure divided the the out-of-sample test set into bins according to their predicted probability to offering training and it compares their average predicted probability of offering training to the average true probability in each bin. Finally, to provide a qualitative assessment, we report the most predictive phrases in the word cloud in Figure F.2.2.

On-the-job training in US online ads

This section describes new summary statistics of on-the-job training posted in US ads. It also compares with survey results on actual training.

Random sample of job vacancies

Even limiting the analysis from 2013 to 2019 and to only those vacancies with non-missing occupation, employer name, and metropolitan statistical area (MSA) code the number of vacancies exceeds the 100 millions. Therefore, to maintain the tractability of the analysis we randomly select 10% of the employers posting at least a vacancy in 2019. This yields a

[5] In Appendix, Figure F.2.2 plots the ROC curve which display the percentage of true positives predicted by the model along the predicted probabilities of offering training.

[6] The performance is similar to that of other recent economic papers using similar machine learning models, such as Ash et al. (2021) with an AUC-ROC of 0.78; Kleinberg et al. (2018) of 0.71; and Mullainathan and Obermeyer (2019) of 0.73.

sample of 12,634,777 unique job vacancies. Figure F.2.2 compares the number of posted vacancy in the full sample and the 10% random sample. We can notice how the two series are well correlated, however, we can also notice that in 2018 there is a significant jump in the number of vacancies collected by BGT, this is due to an improvement in the collecting of online vacancy. To check if the estimates are not driven by the difference in the collection procedure, we have performed the analysis also only on those vacancy posted before 2018.

Comparison with other measures of on-the-job training

We compare the job-ad measure of on-the-job training to two other measures. First, we use BLS data on the typical on-the-job training needed to attain competency in each occupation.[7] The BLS distinguishes six on-the-job training categories based on the occupational description from O*NET: none, short-term/moderate-term/long-term training, residency and apprenticeship.[8] We pool the five categories with some training together, and we aggregate the BLS measures at the SOC 2-digit level by taking the simple average of the corresponding training dummy. Similarly, we compute the average probability of on-the-job training offer from our ML model at the same occupational level. Figure 2.8b shows that the BLS and job-ad measures are positively correlated. The fitted line accounts for the occupational number of vacancies posted within the year 2019. This is illustrated by the marker size in the right-hand panel (b). Furthermore, Figure 2.8c replicates the analysis at a finer level of the SOC occupation classification (5-digit). The binscatter plot confirms the positive relation between the job-ad measure and the BLS index.

[7] The BLS data are available at https://www.bls.gov/emp/tables/education-and-training-by-occupation.htm

[8] Long-term on-the-job training takes more than 12 months; Moderate-term takes more than 1 month and up to 12 months; Short-term on-the-job training takes 1 month or less. See https://www.bls.gov/emp/documentation/education/tech.htm

Second, we use the Survey of Income and Program Participation (SIPP) of 2008. This is the main survey recording employees' answers to on-the-job training related questions. The SIPP describes if each worker has received in the previous year some kind of training to improve her skills and if this training was paid by her employer. Using these two questions we construct the average percentage of workers who have received on-the-job training per US state and compare this estimate with those obtain on BGT data.[9] Figure 2.8d shows the positive relation between the SIPP and job-ad measure.

2.2.2 Labor market competition

A flowering recent literature, both empirical (Azar et al., 2020a,b; Benmelech et al., 2020; Rinz, 2022; Schubert et al., 2020; Marinescu et al., 2021; Azar et al., 2022; Hershbein et al., 2022; Arnold, 2020) and theoretical (Jarosch et al., 2019; Berger et al., 2022; Azkarate-Askasua and Zerecero, 2020) has demonstrated a negative relationship between wages and local labor market concentration. Building on this research, we adopt local labor concentration as our primary measure of labor market competition. The rationale is that an increase in concentration reduces labor supply elasticity, possibly due to a reduction in outside options or worker and job heterogeneity.[10]

The main point is that due to a reduced labor supply, an employer can offer lower wages without fearing the possibility that the worker will change jobs. However, as a corollary, sometimes ignored, lower labor supply works both ways, i.e., an employer in a concentrated market will find it more difficult to hire new workers as they have a lower labor supply elasticity.[11] This decreasing labor supply elasticity in a highly concentrated market leads

[9]There are more recent SIPP surveys: 2014 and 2018. However, unfortunately, these surveys have changed the relevant questions regarding on-the-job training and restricted the sample of respondents. Specifically, the training related questions are asked only to those workers who are not graduated and are below 200% of the poverty line. We have further restrict the SIPP sample to only those workers with an age between 15 and 65 years old that had a paid job during the reference period.

[10]See (Manning, 2003, 2011; Robinson, 1969) for more in-depth information and a review of the literature on monopsony power and its potential sources.

[11]For clarity, although the employer can offer lower wages to incumbent workers, to increase her work-

employers to reduce their labor demand to keep wages low. This idea is observed, for example, in Marinescu et al. (2021) and Berger et al. (2022). Consequently, an employer in concentrated markets would be more willing to offer training when this allows for increasing their labor supply without raising wages.[12] We further detail this mechanism in Section 2.4. In subsection 2.2.2 we define our measure of local labor market concentration, while in section 2.2.2 we compare this measure with other potential proxies of labor market competition, such as unemployment, job creation, and job destruction.

Local labor market concentration measure

To measure the effect of local labor market concentration on the employers' on-the-job training and wage posting decisions, we first have to define the relevant labor market. Most literature represents a local labor market as a combination of a geographical area, a time, and an industry or occupation; see for example (Schubert et al., 2020; Azar et al., 2020b; Marinescu et al., 2021; Hershbein et al., 2022; Rinz, 2022). Following this literature, we define a local labor market as a combination of a year, a SOC 6-digit occupation, and a U.S metropolitan statistical area (MSA).

We use the Burning Glass Technologies (BGT) database of online vacancy postings to measure employer concentration. We calculate the Herfindahl-Hirschman Index (HHI) of the share of vacancies posted by each employer at the local labor market level.

Specifically, we compute the vacancy HHI as the sum of the squared vacancy employer shares for each local labor market, which is defined as the combination of 6-digit SOC occupation, metropolitan statistical area, and year.

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force and hire new workers the employer will have to offer a larger wages. If the employer cannot perfectly wage-discriminate across her workers, a marginal increase in the wages will lead to an increase in all the incumbent wages.

[12]Two recent surveys provide anecdotal evidence on the potential effect of training as an attracting device (Monster, 2021; Gallup, 2021). Monster (2021) found that among workers who recently quit a job, 45% would have remained if they were offered more training, while Gallup (2021) documented that 48% of American workers would switch jobs if the new job provided skill training opportunities.

$$HHI_{o,l,t} = \sum_{i}^{N} \left(\frac{v_{i,o,l,t}}{V_{o,l,t}} \right)^2 \tag{2.1}$$

where $v_{i,o,l,t}$ is the number of vacancies posted by employer i in the local labor market defined by the combination of occupation o, metropolitan statistical area l, and year t; while $V_{o,l,t}$ is the total number of vacancies posted in that local labor market.

Comparison with other measures of labor market competition

We compare our employment HHI measure with other potential proxies of labor market competition: unemployment rate, job creation rate, and job destruction rate.

We use the local unemployment rate from the Local Area Unemployment Statistics (LAUS) program provided by the U.S Bureau of Labor Statistics, measured at the metropolitan statistical area (MSA) and year. The job creation and destruction rates are obtained from the Business Dynamics Statistics (BDS) provided by the U.S. Census and are measured at the combination between a sector (2-digit NAICS code), MSA, and year. The job creation and destruction rates are constructed considering the increase and decrease (respectively) in the share of employment for each establishment in the segment previously defined. For more information on these measures see Appendix D.2.

To compare these measures with our HHI measure, which is defined at the combination between MSA, occupation (6dig SOC), and year; we take the weighted average of our HHI at the same level of the unemployment rate (year × MSA) and of the job creation and destruction rate (year × sector × MSA). Figures 2.8, 2.8, and 2.8 shows that these alternative measures are strictly correlated with the HHI, even when controlling for fixed effects, such as year, MSA, and industry.

Despite the strong correlation, we prefer our HHI measure for two main reasons. First, by virtue of what discuss in Section 2.2.2 and Section 2.4, we consider HHI as a better measure for labor market competition. Second, because HHI can be constructed at the finest level of aggregation, which by virtue of the recent literature that shows how labor markets are very local, we consider a better local labor market definition (Manning and Petrongolo, 2017; Marinescu and Rathelot, 2018; Kaplan and Schulhofer-Wohl, 2017; Le Barbanchon et al., 2021). However, we can see in Appendix D.2 that the results using these alternative measures are in line with our main results.

2.3 Descriptive statistics

Focusing on our representative sample consisting on 10% of the employers posting a vacancy in 2019, Figure 2.8 shows the share of vacancies offering on-the-job training at the monthly and quarterly level. The share of vacancies is slightly increasing over time floating between 25% and 30%. Figure 2.8 plots the average training predicted probability and the HHI across Metropolitan Statistical Areas (MSAs) in 2019. The training map is divided by quartiles: $[0, 0.24)$, (0.24-0.33], (0.33-0.37], and (0.37-0.65]. While for the HHI map, we group the MSA according to the **(alias?)** classification, which defines a market with an HHI of 0-0.15 as low concentrated, 0.15-0.25 moderately concentrated, 0.25-0.35 highly concentrated, and ≥ 0.35 very highly concentrated.

Figure 2.8 shows the logarithmic distribution of the HHI at the local labor market and at vacancy level. While the average job ads is posted in a lowly concentrated labor market, the average local labor market is moderately concentrated, with a mean above log(HHI) = 7, equivalent to an HHI of 0.11 or an Inverse Herfindahl-Hirschman Index (IHHI) of 9.2.[13] The Inverse Herfindahl-Hirschman Index (IHHI) can be interpreted as the number of equal-sized firms that will induce the same observed HHI.[14]

[13]Note that as a standard procedure we have taken the log of the HHI multiplied by 10 000, this is to avoid having negative numbers.

[14]For example, an IHHI of 10 implies that the market has the same HHI that a market consisting of

Figure 2.8 displays the 2019 distribution of the average number of vacancies, the average training probability, and the HHI across 2-digit SOC occupations.

Figure 2.8 show the average predicted training probability according to the level of education and experience demanded in the vacancy posted. One can see that experience and training are negatively correlated. Vacancies demanding many years of experience are unlikely to offer training. About education, it also appears that employers offering training do not request graduate applicants.

Finally, Figure 2.8 provides (left) the average training probability and (right) the share of vacancies providing some information on the wage offered across the HHI quartiles. The figure supports our idea that employers strategically exploit the labor market conditions. Specifically, an employer located in a highly concentrated labor market, given the difficulty to poach workers, will try to attract new workers from other occupations, highlighting the willingness to train them in the new occupation. On the other hand, if an employer is in a lowly concentrated labor market, she can poach workers from her competitors. Thus, she will try to attract these new experienced workers by posting an attractive salary.

2.4 Conceptual framework

Although the main focus of our paper is empirical, to guide the discussion we construct a stylized framework combining a oligopsony model results to a direct search model.

There are a number of models of the labor market in which labor market concentration matters for wages. Specifically, according to the traditional monopsony theory (Robinson, 1969; Manning, 2003) labor market concentration can generate an upward-sloping labor supply curve to individual firms, making for them marginally more expensive to hire workers. Consequently, the most productive firms in highly concentrated market will

10 firms with the same number of employees would have.

reduce their optimal employment causing misallocation inefficiencies.[15]

We include this result of an upward labor supply curve in a direct search model framework similar to Shimer (2005); Faberman and Menzio (2018); Marinescu and Wolthoff (2020), and discuss its predictions.

The model distinguishes firms and workers into two groups, representing the labor market's different occupations. We further allow the possibility for the firms to pay a fixed cost to rule out the difference in productivity that workers have in various occupations. The idea is to address the opportunity for firms to train workers and make them equally productive with already trained workers. Our model shows that firms will opt for training to reduce queuing time to attract valuable applicants.

2.4.1 Setting

We consider a static economy composed by two agents, workers and firms. Both agents are divided into two different segments, characterizing a horizontal heterogeneity in productivity, underlining two different occupations. The rationale behind is that a welder

[15]For a theoretical description see Robinson (1969) and Manning (2003), or more recently Berger et al. (2022). For empirical results on this idea, see Marinescu et al. (2021). An alternative approach, similar in result, is the one in Jarosch et al. (2019), where labor market concentration reduces the number of feasible outside options for workers, as the average worker in a given labor market has few different firms as possible alternative employers. Analogously, labor market concentration reduces the number of suitable candidates for firms. Considering that workers require considerable skills to perform a specific job profitably and that this skill can be properly acquired only through on-the-job training and experience. A dominant firm can only obtain suitable candidates from other firms in its market by poaching its employees. However, as the number of firms in a market decreases, the number of poachable workers also decreases. The same idea of an upward labor supply curve can also be derived from a model à la Burdett and Mortensen (1998), where firms with a larger labor force have to offer higher wages. Therefore, at a high concentration level, i.e., few large firms dominate the market, an employer has to offer marginally higher wages to attract more workers. Although an additional worker will be beneficial, the firms find it more profitable to renounce hiring new workers as this would create upward pressure on the wages, reducing their profits consequently. Note that is the concentration level and not exclusively the number of firms the key to the mechanism. The employment size of a firm depends not only on the wage offered by the same firms but also on the distribution of wages offered by the other competing firms. Thus, for a given firm with a fixed employment share, being in a market with several small or few large firms has a big difference. As in the former case, the distribution of the wages by the competitors will be lower than in the latter case due to the strict link between wages and size.

can not be able to do the job of a lawyer and vice-versa.[16]

2.4.2 Direct search and matching

Firms compete for workers by posting wages that are type-independent $\{w_j\}$. After observing the wages, workers decide to apply to the firm, maximizing their expected payoff based on both the probability of being hired and the wage. Following a standard assumption in the literature of direct search, we assume that workers can apply to only one firm, and firms hire only the best applicant. The assumption of a single application captures the opportunity cost for applying to multiple jobs. However, extending the model and allowing workers to apply to a finite number of firms in the same period will not substantially change the empirical predictions.

We further assume that posted wages are binding, i.e., firms cannot decide to bargain the wage after the match. Moreover, firms can choose to do not to post wages. In this case, for simplicity, we assume that workers correctly predict the average expected wages. However, they are also risk-averse; thus, given the same expected wage, they will prefer to apply to a firm posting wage to a non-posting wage firm.

Finally, we assume that the measure of potential candidates for a firm is proportional to the extent of concentration in that market. The idea behind this assumption is that at a higher concentration, there is a lower labor supply faced by the firm, i.e., a firm finds it more challenging to attract new candidates.[17] A straightforward way to assume it is

[16]Clearly, the model can be extended to account for a broader set of occupations, each of them with a different degree of substitutability. However, this extensions would not change our empirical predictions. Additionally, it can be extended to assume that workers within an occupation are divided into M different types, $m = 1, \ldots, M$. Similarly, in each segment there are N different types, $n = 1, \ldots, N$. These different types depict workers and firms different productivity, a worker $m = 2$ will be more productive than a worker $m = 1$, analogously for the firms.

[17]In this, we differentiate by the standard literature of direct search, which generally uses measures of market tightness such as the unemployment rate. However, as observed recently by Faberman et al. (2017) the majority of job transitions are job-to-job transitions; thus, concentration could be a better-suited proxy for the potential number of workers, including the possibility for employers to poach workers from her competitors.

to consider a search model with an exogenous separation rate and without recall as in Jarosch et al. (2019). In this case, the number of potential candidates for a firm j will be $\delta(1-s_j)$, where δ is the exogenous separation rate and s_j is the employment share of firm j in that market. Therefore, the average number of potential candidates in the market will be:[18]

$$\sum_j s_j \delta(1-s_j) = \delta(1-HHI)$$

2.4.3 Production and Payoffs

A match between a worker (i) and a firm (j) produces $y_{i,j}$, which depends on the quality of the match (i,j). The worker's payoff is the wage w_j, while the firms keeps the remaining output $y_{i,j} - w_j$. Unmatched workers and firms get a null payoff. Therefore, the expected payoff of a worker (i) depends both on the probability to be hired and her productivity.

2.4.4 Symmetric equilibrium and Queue length

As standard in the literature, we consider the symmetric equilibrium where workers and firms of the same type behave identically. This assumption implies that the expected number of applicants of type (i) at a firm (j) follows a Poisson distribution with endogenous mean $q_{i,j}$ which is known as the "queue length", see Shimer (2005).

2.4.5 Benchmark: no training allowed

Assuming an horizontal differentiation, i.e. matches between workers and firms of the same types are always more productive: $y_{1,1} > y_{2,1}$ and $y_{2,2} < y_{2,1}$; the number of applicants that a firm received will depend on the number of workers in her segment and the difference in productivity between working in their own occupation or working in the other one.

[18] Alternatively, an analogous result arises with a Cournot-style oligopsonistic model of labor quantity competition based on differentiated firm-specific amenities in a nested framework that separate within-market and between-market labor supply behavior (Berger et al., 2022).

Intuitively, firms in markets in which they expect few applicants will offer longer queue. Therefore, in more concentrated markets where the number of potential applicants is limited, firms will wait longer to obtain a match. However, if the gap in productivity is relatively small $y_{2,1} - y_{2,2} = \varepsilon$, firms in high concentrated markets will attract also workers from the other market, which in turn reduces their queue time.

Moreover, as posting wages is binding, firms with a short queue, i.e with a few expected number of applicants, will be less willing to post wages. As by posting wages they will preclude themselves to only one time of applicant. If they post a wage low in order to attract also the less productive workers, they will disincentive the matched workers to apply. On the other hand, if the post a wage tailored for the matched workers, they will be bound to pay the same wages also to the less suited matches. Consequently, in high concentrated markets where employers will attract also workers from other segments, we can expect to observe less wage posting.

2.4.6 Extension: Allowing training

Assume now that firms could pay a fixed cost for training their workers. After training, the workers are equally productive in both occupations. As before, two forces are at play: labor market tightness (concentration) and difference in productivity. There will be no training if the differences in productivity and concentration are slight across the two markets. However, suppose the productivity in the more concentrated market is remarkably higher. In that case, offering training will drastically increase the number of applicants for the firms in concentrated markets, which will reduce their lost profits due to the time for finding a suitable candidate. More prominent is the gap in productivity or concentration across the two markets; more significant will be the incentive to train.

Empirical predictions:

1. At higher employer concentration there will be more on-the-job training offers.

2. Higher concentration lowers the probability a vacancy posts wage information.

2.5 Empirical strategy

To estimate the effect of employer concentration on training and wage posting probability, we rely on the following specification:

$$Y_{ijolt} = \gamma \log(HHI_{olt}) + \delta X_{ijolt} + \text{fixed effects} + \varepsilon_{ijolt} \tag{2.2}$$

where subscript i, j, o, l, and t denote respectively vacancy i, employer j, occupation o, MSA l, and year t. $\log(HHI_{olt})$ denotes the log. of the Herfindahl-Hirschman Index (HHI) as defined in Equation 2.1; Y_{ijolt} is the outcome variable, which in the main analysis is either (i) the predicted probability that vacancy i offers on-the-job training, or (ii) a binary variable on whether the vacancy has posted wage information. X_{ijolt} denotes a set of controls at the firm, vacancy, or market level. We saturate the model with the inclusion of different combinations of fixed effects, the preferred specification includes year, MSA, 6-digit SOC occupation code, 2-digit NAICS industry code, and employer fixed. Yet, the results are robust to different combination of fixed effects. We estimate equation 2.2 with standard errors clustered at the local labor market level, combination between a year, MSA, and a 6-digit SOC occupation.

2.5.1 Instrumental variable approach

The use of the concentration measure likely raises endogeneity concerns. An increase in concentration could be driven by the expansion of more productive and larger firms, leading to higher on-the-job training offers or wage information postings. One could think that larger firms have more resources or dedicated human resources departments, which might affect the provision of training or the quality of the job ads text, for example, by including more information. On the other hand, an increase in concentration could also be driven by worsening the business conditions in that local labor market, leading to a reduction of training provisions. Therefore, although the issues on the endogeneity of the concentration measure, the direction of the bias is ambiguous. To address the endogeneity issue, we follow the strategy of Schubert et al. (2020) and use an instrumental variable approach based on the granular instrumental variable approach of Gabaix and Koijen (2020) and a "double shift-share Bartik" approach (Chodorow-Reich and Wieland, 2020).

Following the Bartik strategy, we can decompose the variation in the vacancy concentration for an occupation o, location l, and year t as a function of the previous vacancy share of each firm j ($s_{j,o,l,t-1}$) and its growth rate $g_{j,o,l,t}$ with respect to the market vacancy growth rate $g_{o,l,t}$. Formally,

$$\Delta HHI_{i,l,t} = \sum_j s^2_{j,o,l,t} - \sum_j s^2_{j,o,l,t-1} = \sum_j s^2_{j,o,l,t-1} \left(\frac{(1+g_{j,o,l,t})^2}{(1+g_{o,l,t})^2} - 1 \right) \tag{2.3}$$

where $s^2_{j,o,l,t}$ is the employment squared share of employer j in the occupation o, metropolitan statistical area l and year t; $\tilde{g}_{jot}$ is the national vacancy growth of firm j in occupation o and year t leaving out metropolitan statistical area l.

Following Schubert et al. (2020), we instrument the vacancy growth for each firm j in occupation o and location l with the national vacancy growth of that firm for that occupation in the other locations. Formally, the instrument is as follows:

$$\log(HHI^{\text{instr.}}_{o,l,t}) = \log \left[\sum_j s^2_{j,o,l,t-1} \left(\frac{(1+\tilde{g}_{j,(-l),o,t})^2}{(1+\tilde{g}_{o,l,t})^2} - 1 \right) \right] \tag{2.4}$$

where $\tilde{g}_{olt}$ is the vacancy growth for MSA l, occupation o, and year t predicted by the predicted growth in vacancy in occupation i for each employer j

$$\tilde{g}_{olt} = \sum_j \sigma_{jolt} \tilde{g}_{j,o,(-l),t}$$

To avoid that relatively small employers drive the instrument, we construct $\tilde{g}_{j,o,(-l),t}$ considering only "large employers", i.e., those employers with vacancies in occupation o in at least five metropolitan statistical areas in that year t, as in Schubert et al. (2020). This restriction implies that the sum of the vacancies shares computed in the instrument construction does not sum up to 1. To address this issue, we add an "exposure control", defined as the sum of these large employers' squared vacancy shares. Given our econometric model, firms' vacancy growth should affect training only through vacancy concentration, which is a quadratic term. However, firms' vacancy growth could linearly affect local labor market features, such as labor demand and training decisions. Therefore, following the literature, we include two additional controls: (i) the actual vacancy growth rate in occupation o, location l, at year t ($g_{o,l,t}$) and (ii) the predicted vacancy growth rate $\tilde{g}_{o,l,t}$. Conceptually, this should capture the potential direct linear effects of firms' vacancy growth on training decisions.

2.6 Main Results

This section tests our main empirical predictions that local labor market concentration (1) increases the on-the-job training provision and (2) decreases the share of vacancies posting wage information.

Table 2.4 reports the estimates of labor market concentration on the predicted probability for a vacancy to offer training, as specified in Equation 2.2. Columns 1, 2, and 3 show the basic OLS estimates considering different specifications of fixed effects: Column 1 considers year, MSA, and occupation fixed effects; Column 2 adds sector (2digit

NAICS) fixed effect, and Column 3 adds employer fixed effects. Columns 4, 5, and 6 adopt the instrumental variable approach described in Section 2.5 and use the same fixed effect specifications of Columns 1, 2, and 3, respectively. On-the-job training is positively and significantly correlated with labor market concentration across all six specifications. Moreover, the IV estimates are notably larger in magnitude, suggesting that some combination of omitted variable bias or measurement error biases the coefficients toward zero in the basic OLS regressions.[19] Additionally, it is worth noting as the results are robust to the inclusion of employer fixed effects, hinting that employers consider the labor market conditions in their hiring decisions.

To give a sense of the average results of labor market concentration on training offers, consider Table 2.4, Column (6), which is the IV specification including year, MSA, occupation, industry, and employer fixed effects. This specification implies that an interquartile range change in the HHI vacancy distribution, which consists in a vacancy posted in the 25th percentile of the HHI distribution (0.011) to the 75th percentile (0.078), increases the probability that that vacancy offers training by 1.4 percentage points, consisting of almost 5 percent increase of the likelihood that an employer provides on-the-job training with respect to the mean.[20]

Tables 2.5 shows the analogous impact of local labor market concentration on the probability that an employer posts wage information. in both the OLS and the IV specifications an increase in HHI reduces the probability of wage information posting. All coefficients are

[19] The first stage regressions are reported in Table T.2.1.

[20] The percentage points are computed as: $[log(p75) - log(p25)] * \hat{\gamma} * 100$. The percent effect ($\beta_{\%}$) with respect to the mean is computed as follows:

$$\beta_{\%} = (\hat{\gamma} * log(\delta + 1))\frac{100}{\text{MDV}}$$

$$\text{where} \qquad \delta = \frac{p75(HHI) - p25(HHI)}{p25(HHI)}$$

where $\hat{\gamma}$ is the estimated coefficient, p75(HHI) and p25(HHI) are taken from Table 2.2, and MDV is the mean of the dependent variable, i.e. predicted training probability, taken from Table 2.4.

also all statistically significant at the 1 percent level. Considering our preferred specification (Column, 6), it documents that an interquartile range increase in the HHI decreases the probability that a vacancy provides wage information by 1.3 percentage points, consisting of a 10 percent decrease with respect to the mean.

2.7 Additional effects of employer concentration

In this section, we investigate other potential effects that employer concentration may have. First, we provide evidence that employer concentration decreases the years of experience and education required. Second, we show that vacancies in highly concentrated markets have more words, but these words have fewer syllables. Moreover, those vacancies demanded more intellect personality traits than vacancies in low concentrated markets.

2.7.1 Experience and Education demanded

At high concentration levels, given the limited presence of suitable job seekers in that market and the difficulty of attracting workers from other markets, employers may find it more challenging to find job candidates. For this reason, they could reduce the requirements requested to fill the vacancy. Thus, for example, an employer could reduce the years of experience or education generally required to attract even those workers who work in other occupations or who can be taught the necessary missing skills through on-the-job training. This effect is indeed what we observed.

Using the same empirical strategy described in Section 2.5, in Table 2.6, we show how the years of experience and education demanded in the vacancies decrease significantly as the level of concentration increases. In particular, the first two columns show how, if the concentration increases by an interquartile range, the years of experience demanded decreases between 0.05 (OLS) and 0.04 (IV) index points, which consists of a reduction of around 4% and 3% with respect to the mean, respectively. Similarly, with the same increase in HHI, our education index variable loses 0.04 (OLS) and 0.1 (IV) index points, representing a reduction of 3% and 8%, respectively. Finally, the last two columns show how the same increase in concentration reduces the probability that the job advertisement requires at least a Bachelor's degree of about 1.2 and 2.5 percentage points, consisting of a reduction of 5% and 9%, respectively.[21]

2.7.2 Job text complexity and type of skill demanded

Does the concentration level in a local labor market affect the amount of information and the complexity of the job ad text? To answer this question, we consider four different variables (1) the log of the number of words in the job ad text, (2) the average number of syllables per word, and if the job ad text has some words linked to specific personality traits. In this regard, we distinguished between (3) intellect traits and (4) non-intellect traits. The intellect traits are identified by keywords such as intellectual, complex, creative, imaginative, and innovative. On the other hand, the non-intellectual traits concern more traits like conscientiousness, agreeableness, and surgency; determined by words such as talkative, assertiveness, cooperative, kind, neat, systematic, practical, sympathetic.

Table 2.7 and Table 2.8 provides the OLS and IV estimates for each dependent variable, respectively, following the empirical strategy described in section 2.5. As concentration increases, the number of words in the job ad's text increases while the number of syllables per word decreases. The results are significant and robust in both specifications (OLS and IV), except for the number of words variable that loses significance in the IV model. These results suggest that as concentration increases, employers increase the informa-

[21]The experience variable is approximated at the year, 0 is no experience demanded, 1 is less or equal than 1 year of experience, 2 more than 1 but less or equal than 2 years of experience, and so on. The education variable takes values: 0 if no qualification required, 1 if High School diploma, 2 if Associate's degree, 3 if Bachelor's degree, 4 if Master's degree, and 5 if PhD. Graduate takes value 1 if education takes value greater or equal than 3.

tion provided to candidates and tend to use simpler words underlined by fewer syllables. Assuming that workers from other occupations require more information because they are less aware of that specific occupation's job features and tasks. These outcomes seem to support the hypothesis that employers are trying to attract workers from different occupations when they are located in highly concentrated markets.

Finally, in the same Tables 2.7 and 2.8, we can observe that employers in highly concentrated markets demand more intellectual traits. The effect is significant and robust to both specifications. One rationale could be that intellect traits can be more helpful in enabling workers to learn skills faster and better. If the employers plan to train her new workers, she would like workers who learn new competencies more quickly and thus have more intellect traits.

2.8 Conclusion

We have examined the effects of labor market competition on employer-provided training decisions and on their decision on posting wages. Taking advantage of the information disclosed by employers in the job vacancy text, we develop a ML measure of the probability that a vacancy is offering on-the-job training. We investigate whether the different level of labor market competition, measured as vacancy concentration, affects the employer's decision to provide training and disclose wage information. The empirical evidence documents how employers increase their training offers at a lower level of labor competition but decrease the probability of revealing wage information. We further observe that employers have lower requirements regarding experience and education at a lower level of labor competition.

The paper adds to the literature by developing a new way to measure employer-provided training and contributes to the literature by examining the effects of labor market competition. Our measure of employer-provided training, contrary to the survey-based measures, can be quickly updated and used in the universe of online job postings. Our findings are consistent with the classical monopsony theory's upward slope labor supply curve to wages. Despite employers could still extract significant wage markdowns from workers, they reduce their labor demand to keep wages low. This upward labor supply curve to wage encourages employers to increase their labor supply by providing training or reducing their education or experience requirements. Overall, this paper has clear implications for policymakers, showing that recruitment behavior differs in monopsonistic markets. Consequently, labor market competition should be considered when designing policies to mitigate anticompetitive or antidiscrimination practices, as well as labor market policies aimed at bridging the skill gap of displaced workers.

2.9 List of Tables and Figures

2.9.1 List of Tables

Table 2.1: Out-of-Sample Metrics for Predicting Training offers

Accuracy	0.795	True Negatives (TN)	1072
F1	0.708	False Negatives (FN)	244
AUC-ROC	0.862	True Positives (TP)	487
Recall	0.666	False Positives (FP)	157
Precision	0.756		

Notes: The table reports the test-set evaluation metrics. Accuracy is the proportion of out-of-sample observation for which the machine-predicted model correctly predict the true label. Recall is the proportion of correct predicted training within the set of vacancies actually offering training (TP/(TP+FN)). Precision instead is the percentage of correct training predictions relative to the total number of training predictions (TP/(TP+FP)). F1 is the weighted harmonic mean of precision and recall. The AUC-ROC identifies the Area Under the Receiver Operating Characteristics.

Table 2.2: Summary Statistics

	N	mean	sd	25 pct.	median	75 pct.	95 pct.
Training prob.	12,633,515	0.292	0.268	0.083	0.183	0.439	0.873
Wage info.	12,634,279	0.146	0.353	0.000	0.000	0.000	1.000
HHI	12,634,279	0.082	0.150	0.011	0.029	0.078	0.360
log(HHI)	12,634,279	-3.511	1.426	-4.534	-3.551	-2.547	-1.022
HHI(market level)	773,677	0.266	0.269	0.078	0.167	0.344	1.000
log(HHI_market)	773,677	-1.849	1.115	-2.557	-1.792	-1.068	0.000
Education [0,5]	12,634,279	1.181	1.324	0.000	1.000	3.000	3.000
NA	12,634,279	0.440	0.496	0.000	0.000	1.000	1.000
HighSchool	12,634,279	0.248	0.432	0.000	0.000	0.000	1.000
Associate	12,634,279	0.046	0.210	0.000	0.000	0.000	0.000
Bachelor	12,634,279	0.232	0.422	0.000	0.000	0.000	1.000
Master	12,634,279	0.025	0.155	0.000	0.000	0.000	0.000
PhD	12,634,279	0.009	0.097	0.000	0.000	0.000	0.000
Experience [0,5]	12,634,279	1.374	1.798	0.000	0.000	2.000	5.000
NA	12,634,279	0.507	0.500	0.000	1.000	1.000	1.000
$\leq$ 1 year	12,634,279	0.157	0.364	0.000	0.000	0.000	1.000
2 years	12,634,279	0.097	0.296	0.000	0.000	0.000	1.000
3 years	12,634,279	0.074	0.261	0.000	0.000	0.000	1.000
4 years	12,634,279	0.025	0.156	0.000	0.000	0.000	0.000
$\geq$ 5 years	12,634,279	0.140	0.347	0.000	0.000	0.000	1.000
unemploy. rate	12,615,947	4.619	1.566	3.550	4.275	5.300	7.600
log. avg. OES Wages	8,407,096	3.216	0.542	2.769	3.157	3.625	4.143
log BGT wages	1,845,306	10.696	0.585	10.243	10.636	11.082	11.716
High skill occ.	12,634,279	0.531	0.499	0.000	1.000	1.000	1.000
No Words	12,633,515	338.293	212.301	200.000	310.000	436.000	694.000
Avg no Syllables	12,630,562	2.132	0.212	2.015	2.157	2.269	2.418

Sample: all vacancies posted between 2013-2019, by a random sample of 10% of all the employers posting vacancy 2019.
Note: Each observation consists in a vacancy. This table displays the summary statistics. The training probability defines the probability that a vacancy is offering training, which is measured using our machine learning algorithm. Wage Info determines whether the vacancy is posting any information regarding the wages proposed. The HHI (Herfindahl-Hirschman index) is the vacancy employer concentration in the local labor market where the vacancy is posted. Each market is defined as the combination of an occupation (6-digit SOC code), Metropolitan Statistical Area (MSA), and year level. The unemployment rate is the BLS Local Area Unemployment Statistics (LAUS), measured at the same market level definition of the HHI. *log. avg. OES wage* is the logarithm of the average wage in the same local labor market, obtained from the BLS Occupational Employment and Wage Statistics (OEWS). The *log. avg. BGT wage* is instead the log. of the average between the min and max yearly wage displayed in the vacancy text. *High skill occ.* defines whether the vacancy is in high skilled occupations, which are those in the 1-3 digit SOC category. *No. Words* counts the number of words in the job ad text, while *Avg. no. Syllables* is the average number of syllables of all the words in the job ad text.

Table 2.3: Summary Statistics by Predicted Training

	No Training.		Training		
	mean	sd	mean	sd	diff.
Wage Info.	0.141	0.348	0.163	0.370	-0.022
HHI	0.079	0.146	0.093	0.166	-0.014
log(HHI)	-3.554	1.426	-3.353	1.415	-0.201
Education					
NA	0.430	0.495	0.477	0.499	-0.047
HighSchool	0.222	0.416	0.343	0.475	-0.121
Associate	0.047	0.211	0.043	0.203	0.004
Bachelor	0.262	0.440	0.120	0.324	0.143
Master	0.028	0.165	0.013	0.113	0.015
PhD	0.011	0.103	0.005	0.069	0.006
Experience [0,5]	1.497	1.881	0.929	1.366	0.568
Missing	0.499	0.500	0.535	0.499	-0.036
$\leq$ 1 year	0.132	0.339	0.247	0.431	-0.115
2 years	0.096	0.294	0.101	0.301	-0.005
3 years	0.082	0.274	0.045	0.208	0.036
4 years	0.028	0.166	0.013	0.114	0.015
$\geq$ 5 years	0.163	0.369	0.058	0.235	0.105
unemploy. rate	4.620	1.555	4.613	1.605	0.007
log. avg. OES Wage	3.259	0.548	3.067	0.492	0.192
log. avg. BGT Wage	10.701	0.592	10.678	0.563	0.024
High skill occ.	0.566	0.496	0.403	0.490	0.163
No. Words	322.462	209.167	395.821	213.663	-73.359
Avg. no. Syllables	2.154	0.215	2.052	0.177	0.102
Observations	9907234		2726281		12633515

Sample: all vacancies posted between 2013-2019, by a random sample of 10% of all the employers posting vacancy 2019.

Note: Each observation consists in a vacancy. This table displays the summary statistics. The training probability defines the probability that a vacancy is offering training, which is measured using our machine learning algorithm. Wage Info determines whether the vacancy is posting any information regarding the wages proposed. The HHI (Herfindahl-Hirschman index) is the vacancy employer concentration in the local labor market where the vacancy is posted. Each market is defined as the combination of an occupation (6-digit SOC code), Metropolitan Statistical Area (MSA), and year level. The unemployment rate is the BLS Local Area Unemployment Statistics (LAUS), measured at the same market level definition of the HHI. *log. avg. OES wage* is the logarithm of the average wage in the same local labor market, obtained from the BLS Occupational Employment and Wage Statistics (OEWS). The *log. avg. BGT wage* is instead the log. of the average between the min and max yearly wage displayed in the vacancy text. *High skill occ.* defines whether the vacancy is in high skilled occupations, which are those in the 1-3 digit SOC category. *No. Words* counts the number of words in the job ad text, while *Avg. no. Syllables* is the average number of syllables of all the words in the job ad text.

Table 2.4: Estimates of labor market concentration on predicted training probability

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
log(HHI)	0.0101***	0.0101***	0.0042***	0.0140***	0.0145***	0.0072***
	(0.0007)	(0.0007)	(0.0005)	(0.0029)	(0.0032)	(0.0023)
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓	✓	✓
SOC_6d FE	✓	✓	✓	✓	✓	✓
NAICS_2d FE		✓	✓		✓	✓
Employer_FE			✓			✓
Controls-IV				✓	✓	✓
MDV	0.294	0.304	0.305	0.288	0.298	0.299
mean(HHI)	0.067	0.071	0.071	0.066	0.069	0.069
std(log(HHI))	1.357	1.341	1.340	1.340	1.326	1.325
R2	.205	.221	.472	.	.	.
F	.	.	.	1,258	1,238	1,370
no employers	121,382	94,893	62,390	93,924	72,733	45,937
N	12,092,827	10,687,657	10,655,154	7,266,614	6,428,006	6,401,210

Sample: all vacancies posted between 2013-2019, by a random sample of 10% of all the employers posting vacancy 2019. Notes: Each observation consists in a vacancy. This table reports the TSLS and OLS regression outputs using as dependent variable *Training*, which defines the estimated probability that that vacancy is offering on-the-job training. The independent variable is the log of the employment HHI, measured at the occupation (6-digit SOC code), Metropolitan Statistical Area (MSA), and year level. The "Control-IV" identifies the exposure, vacancy growth, and predicted vacancy growth controls as described in Section 2.5. MDV reports the Mean of the Dependent Variable. F shows the Kleibergen-Paap F Statistics from the regression. Standard errors are clustered at the market level, which consists of the combination between MSA, occupation, and year. ***, **, and * indicate significance level at the 1%, 5%, and 10% level, respectively.

Table 2.5: Estimates of labor market concentration on wage information

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
log(HHI)	-0.0169***	-0.0154***	-0.0063***	-0.0222***	-0.0192***	-0.0066***
	(0.0008)	(0.0008)	(0.0006)	(0.0033)	(0.0033)	(0.0025)
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓	✓	✓
SOC_6d FE	✓	✓	✓	✓	✓	✓
NAICS_2d FE		✓	✓		✓	✓
Employer_FE			✓			✓
Controls-IV				✓	✓	✓
MDV	0.144	0.133	0.132	0.138	0.128	0.126
mean(HHI)	0.067	0.071	0.071	0.066	0.069	0.069
std(log(HHI))	1.357	1.341	1.340	1.340	1.326	1.325
R2	.124	.196	.418	.	.	.
F	.	.	.	1,259	1,238	1,370
no employers	121,382	94,893	62,390	93,924	72,733	45,937
N	12,093,571	10,688,366	10,655,863	7,267,157	6,428,522	6,401,726

Sample: all vacancies posted between 2013-2019, by a random sample of 10% of all the employers posting vacancy 2019.
Notes: Each observation consists in a vacancy. This table reports the TSLS and OLS regression outputs using as dependent variable *Wage*, which defines whether that vacancy is posting wage information. The independent variable is the log of the employment HHI, measured at the occupation (6-digit SOC code), Metropolitan Statistical Area (MSA), and year level. The "Control-IV" identifies the exposure, vacancy growth, and predicted vacancy growth controls as described in Section 2.5. MDV reports the Mean of the Dependent Variable. F shows the Kleibergen-Paap F Statistics from the regression. Standard errors are clustered at the market level, which consists of the combination between MSA, occupation, and year. ***, **, and * indicate significance level at the 1%, 5%, and 10% level, respectively.

Table 2.6: OLS estimates of labor market concentration on experience and education demanded

	Experience		Education		Graduate	
	OLS	IV	OLS	IV	OLS	IV
log(HHI)	-0.0242***	-0.0199*	-0.0192***	-0.0498***	-0.0064***	-0.0131***
	(0.0026)	(0.0111)	(0.0022)	(0.0093)	(0.0010)	(0.0042)
MDV	1.362	1.413	1.186	1.216	0.262	0.275
mean(HHI)	0.071	0.069	0.071	0.069	0.071	0.069
std(log(HHI))	1.340	1.325	1.340	1.325	1.340	1.325
R^2	0.371	.	0.458	.	0.458	.
F	.	1,370	.	1,370	.	1,370
no employers	62,390	45,937	62,390	45,937	62,390	45,937
N	10,655,863	6,401,726	10,655,863	6,401,726	10,655,863	6,401,726

Sample: all vacancies posted between 2013-2019, by a random sample of 10% of all the employers posting vacancy 2019.
Note: Each observation consists in a vacancy. This table reports the OLS and IV regression outputs using as dependent variables: (1) *Experience*, which is an index variable that takes values 0 if no experience demanded (or missing), 1 if "≤ 1 year", 2 if 2 years, 3 if 3 years, 4 if 4 years, 5 if 5 or more years). (2) *Education*, which is an index variable that takes values 0 if no education or missing, 1 if High School diploma, 2 if Associate's degree, 3 if Bachelor's degree, 4 if Master's degree, and 5 if PhD. (3) *Graduate* that takes value 1 if the vacancy demanded at least a Bachelor's degree, 0 otherwise; those vacancies with missing information on the education requirement are not included. The independent variable is the log of the employment HHI, measured at the occupation (6-digit SOC code), Metropolitan Statistical Area (MSA), and year level. All the regressions uses year, SOC 6-digit, MSA, NAICS 2-digit, and employer fixed effects. Standard errors are clustered at the market level, which consists of the combination between MSA, occupation, and year.

Table 2.7: OLS estimates of labor market concentration on the job ad text information

	log. no. words	Avg. Syllables	Intellect	Non-Intellect Personality
log(HHI)	0.0123***	-0.0024***	0.0024***	0.0031***
	(0.0019)	(0.0003)	(0.0009)	(0.0010)
MDV	5.628	2.129	0.291	0.413
mean(HHI)	0.071	0.071	0.071	0.071
std(log(HHI))	1.340	1.340	1.340	1.340
R^2	0.310	0.578	0.331	0.288
no employers	62,390	62,390	62,390	62,390
N	10,652,695	10,652,695	10,655,863	10,655,863

Sample: all the vacancies posted between 2013-2019, by a random sample of 10% of all the employers posting vacancy 2019.
Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables: (1) *No. Words*, which counts the number of words in the job ad text; (2) *Average Syllables*, which measures the average number of syllables each word in the job ad text has. (3) *Intellect* which identifies if a vacancy is requiring some intellectual skills; while *Non-intellect* if the vacancy is demanding a skill which is not directly related to intellect, but more on agreeableness, conscientiousness, and surgency. The independent variable is the log of the employment HHI, measured at the occupation (6-digit SOC code), Metropolitan Statistical Area (MSA), and year level. All the regressions uses year, SOC 6-digit, MSA, NAICS 2-digit, and employer fixed effects. Standard errors are clustered at the market level, which consists of the combination between MSA, occupation, and year.

Table 2.8: IV estimates of labor market concentration on text information

	log. no. words	Avg. Syllables	Intellect	Non-Intellect Personality
log(HHI)	0.0110	-0.0080***	0.0078**	0.0084**
	(0.0084)	(0.0012)	(0.0037)	(0.0041)
MDV	5.619	2.132	0.294	0.408
mean(HHI)	0.069	0.069	0.069	0.069
std(log(HHI))	1.325	1.325	1.325	1.325
F	1,369	1,369	1,370	1,370
no employers	45,937	45,937	45,937	45,937
N	6,400,211	6,400,211	6,401,726	6,401,726

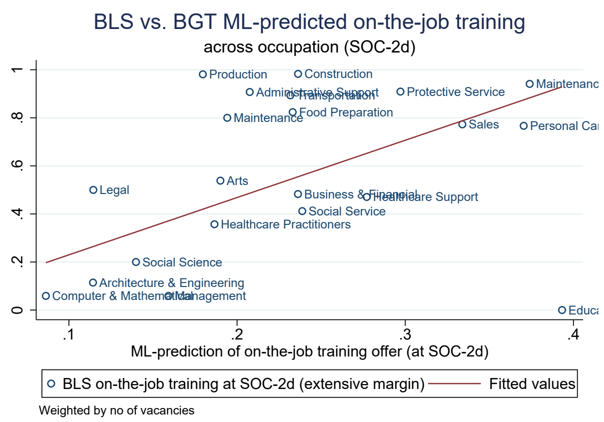
Sample: all the vacancies posted between 2013-2019, by a random sample of 10% of all the employers posting vacancy 2019.

Note: Each observation consists in a vacancy. This table reports the 2SLS IV regression outputs using as dependent variables: (1) *No. Words*, which counts the number of words in the job ad text; (2) *Average Syllables*, which measures the average number of syllables each word in the job ad text has. (3) *Intellect* which identifies if a vacancy is requiring some intellectual skills; while *Non-intellect* if the vacancy is demanding a skill which is not directly related to intellect, but more on agreeableness, conscientiousness, and surgency. The independent variable is the log of the employment HHI, measured at the occupation (6-digit SOC code), Metropolitan Statistical Area (MSA), and year level. All the regressions uses year, SOC 6-digit, MSA, NAICS 2-digit, and employer fixed effects. Standard errors are clustered at the market level, which consists of the combination between MSA, occupation, and year.

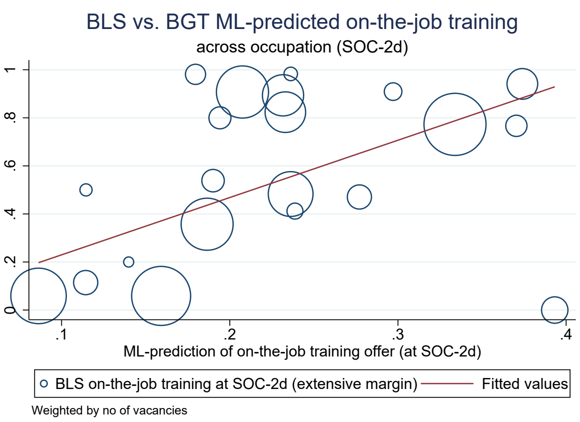
2.9.2 List of Figures

Figure 2.8: Comparison btw BLS, SIPP and BGT measures of on-the-training

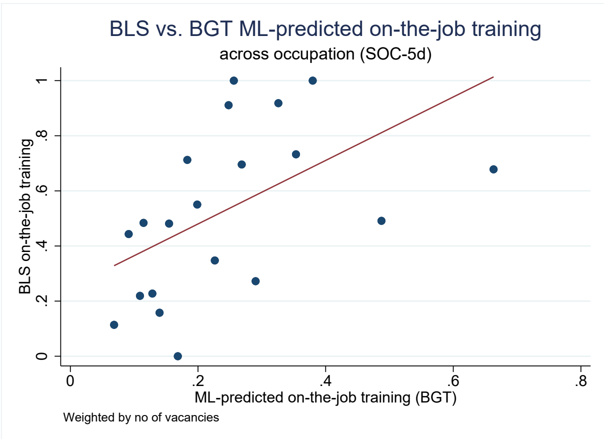
(a) 2-digit SOC



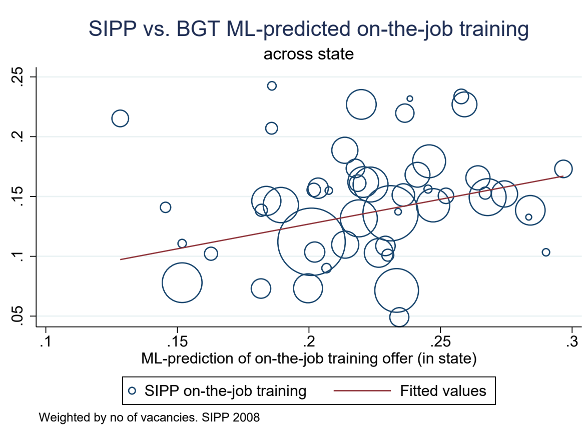
(b) 2-digit SOC



(c) 5-digit SOC

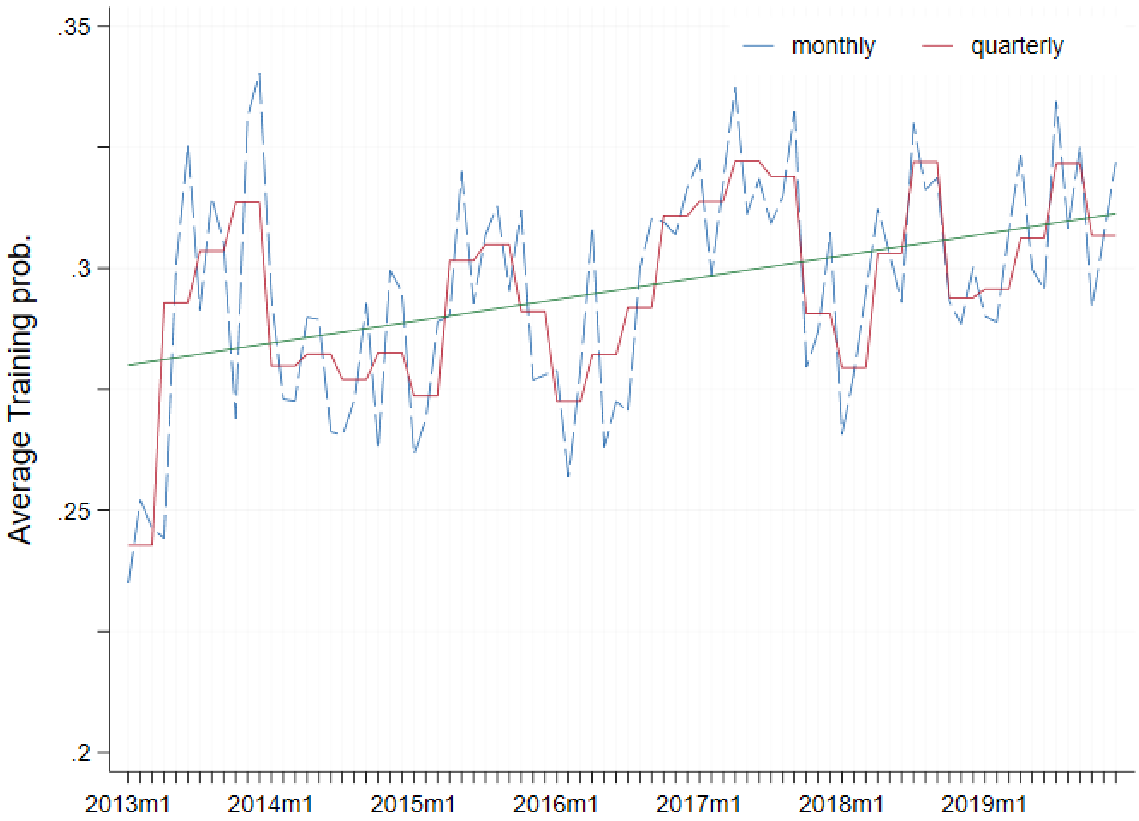


(d) US states



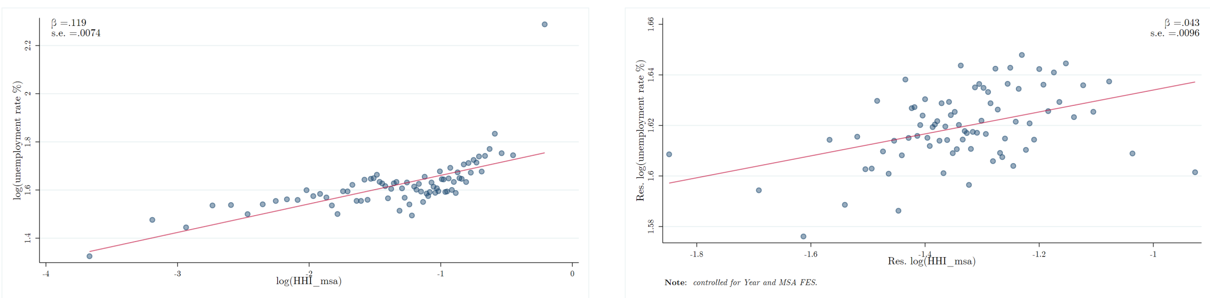
Note: This Figure compares various on-the-job training measures. Our new measure obtained from BGT job ads is on the X axis, while Panels 2.8b, 2.8c, have the BLS measure on the y-axis. We look at the correlation across SOC occupations at the 2-digit level in Panels 2.8b and at the 5-digit level in Panel 2.8c. Occupations are weighted by their number of job ads posted in 2019.

Figure 2.8: On-the-training offer (BGT)



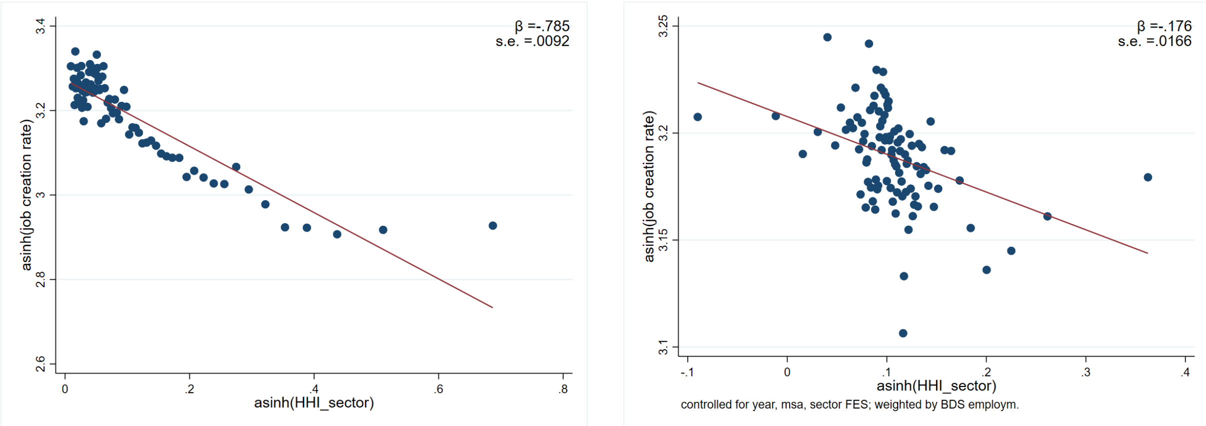
Note: This Figure plots both the monthly and quarterly time series evolution of the share of vacancies offering on-the-job training in our random sample consisting of all the vacancies posted by 10% of the employers posting vacancies in 2019.

Figure 2.8: Unemployment rate: Binned scatter plots



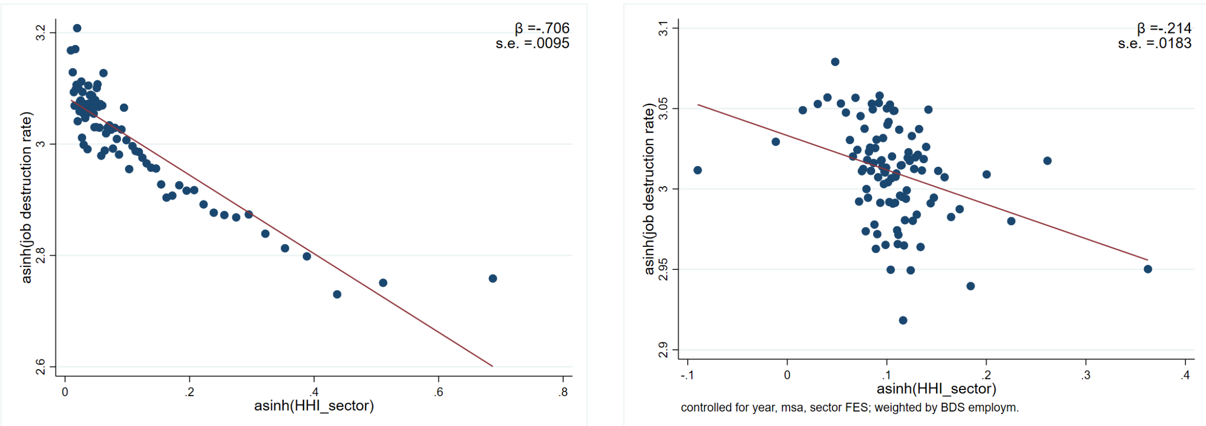
Note: Binned scatter plots between the LAUS unemployemnt rate and log HHI_MSA, for the years 2013-2019. An observation is a combination between a year, and MSA.

Figure 2.8: Job creation rate: Binned scatter plots



Note: Binned scatter plots between the BDS job creation rate and log HHI_sector, for the years 2013-2019. An observation is a combination between a year, MSA, and sector (NAICS-2d). Asinh stands for "Inverse Hyperbolic Sine Transformation" function. Both plots are weighted by the employment size of the market (BDS data).

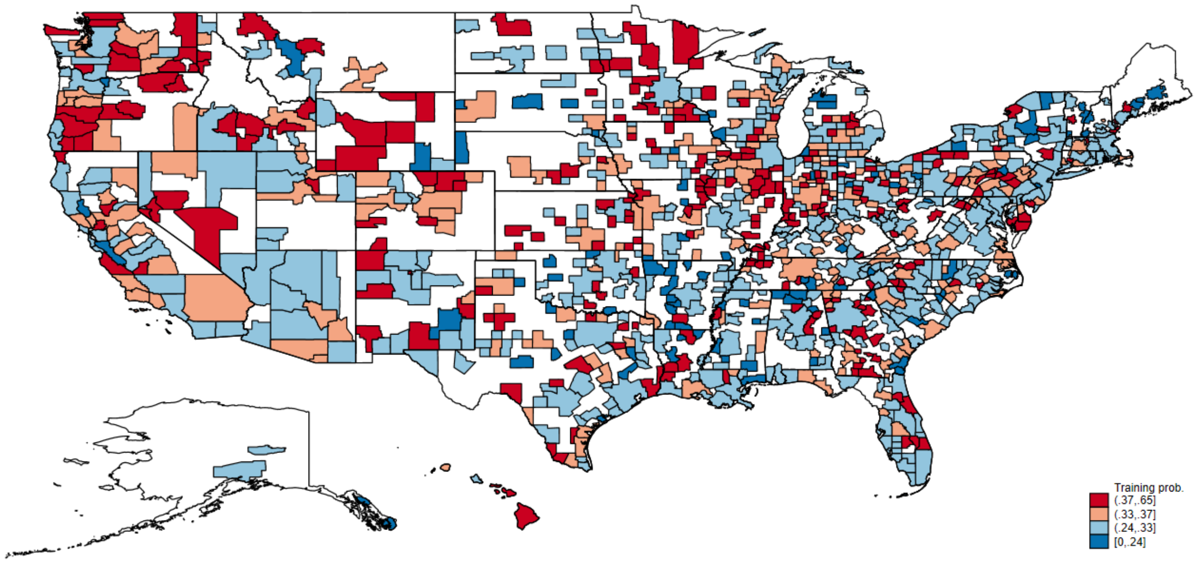
Figure 2.8: Job destruction rate: Binned scatter plots



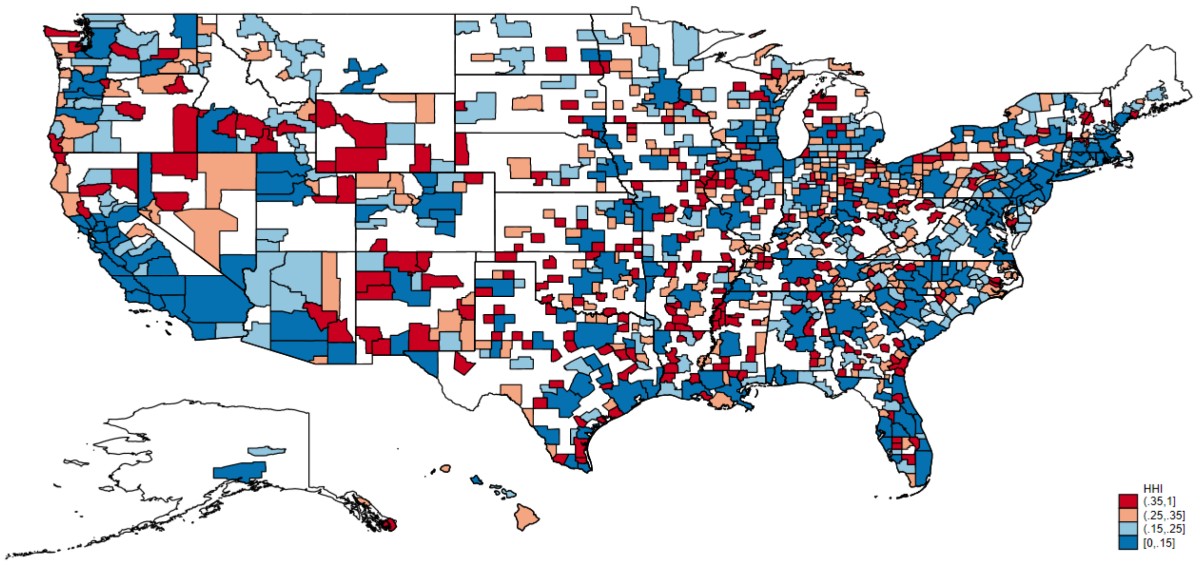
Note: Binned scatter plots between the BDS job destruction rate and log HHI_sector, for the years 2013-2019. An observation is a combination between a year, MSA, and sector (NAICS-2d). Asinh stands for "Inverse Hyperbolic Sine Transformation" function. Both plots are weighted by the employment size of the market (BDS data).

Figure 2.8: On-the-training offer and HHI concentration across MSA

(a) Average training predicted probability



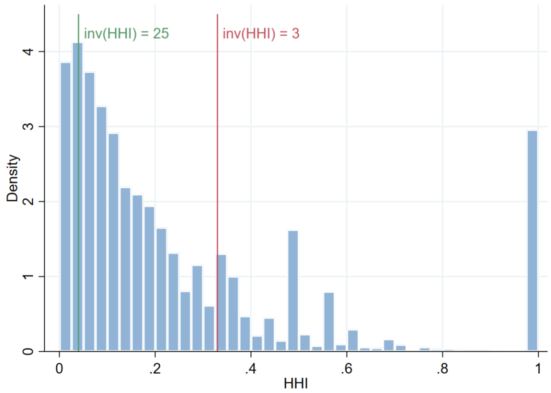
(b) Average HHI



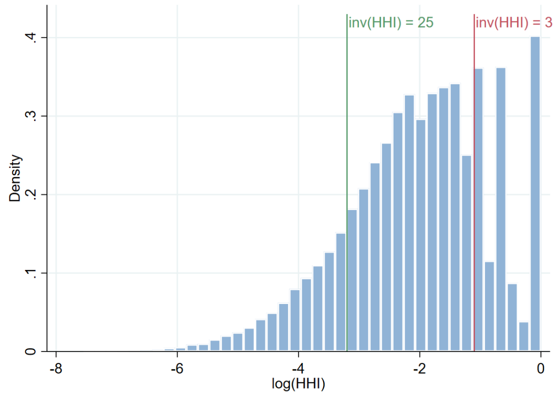
Note: These Figures plot the average training predicted probability (Panel 2.8a) and HHI (Panel 2.8b) across MSAs for the year 2019.

Figure 2.8: Employment concentration in the local labor markets

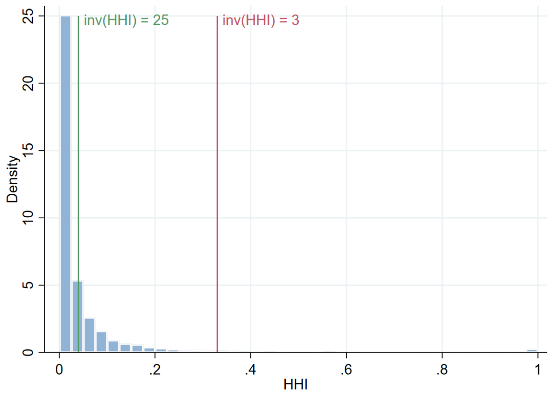
(a) *Average across Markets, level*



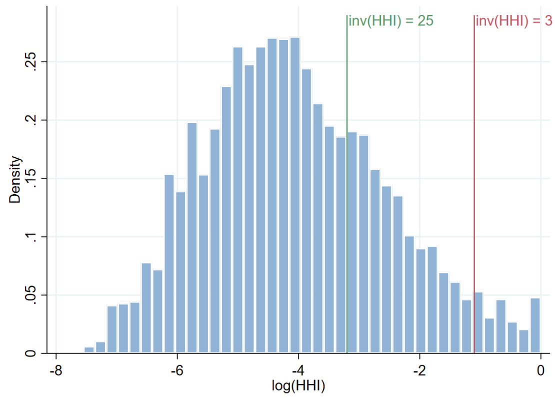
(b) *Average across Markets, logarithm*



(c) *Average across Job Ads, level*



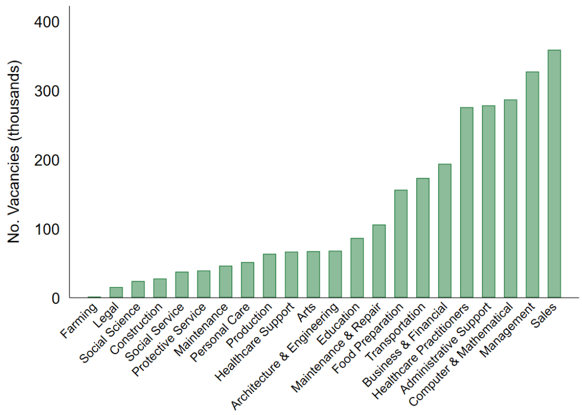
(d) *Average across Job Ads, logarithm*



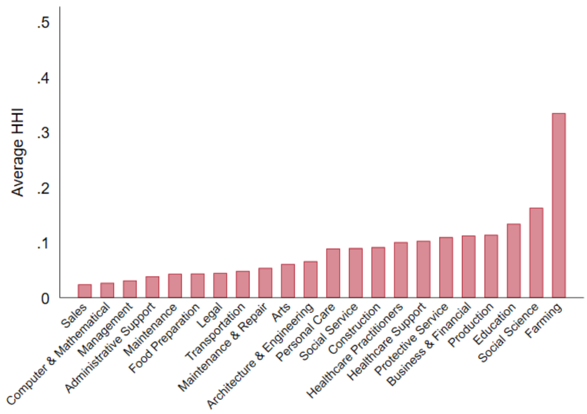
Sample: all vacancies posted in 2019, by a random sample of 10% of all the employers posting vacancy in 2019.
Note: The HHI is computed at the local labor market level, which is defined as a combination of MSA, 6-digit SOC code, and year. The two graphs in the top of the figure are calculated taking the average across local labor market. The two graphs in the bottom of the figure are calculated taking the average across job ads. The inv(HHI) defines the Inverse Herfindahl-Hirschman Index, which can be interpreted as the number of equally sized firms that will obtain the same HHI.

Figure 2.8: On-the-training offer and HHI concentration across 2-digit occupations

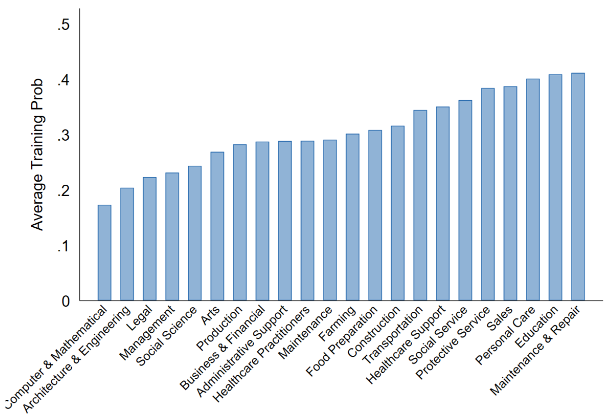
(a) Average number of vacancies



(b) Average HHI



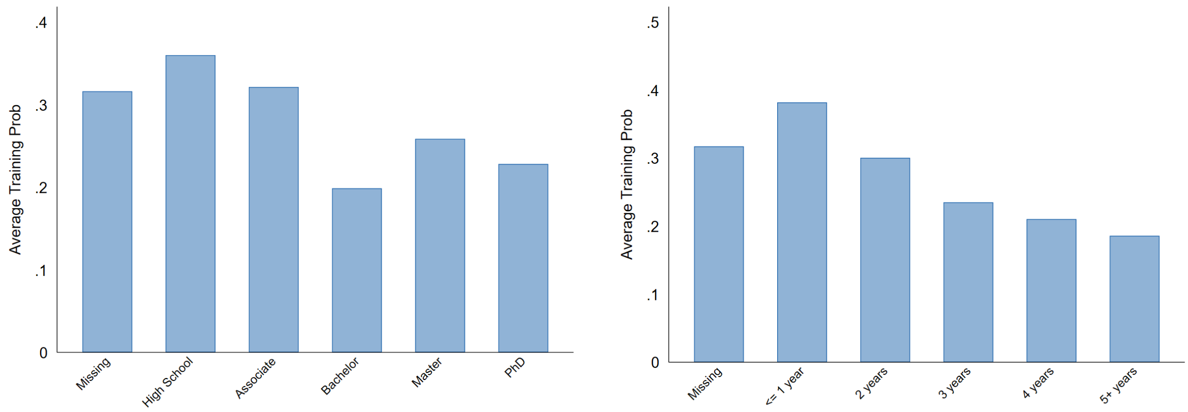
(c) Average training predicted probability



Note: These Figures plot the average number of vacancies, training predicted probability, and HHI across 2-digit SOC codes for the year 2019.

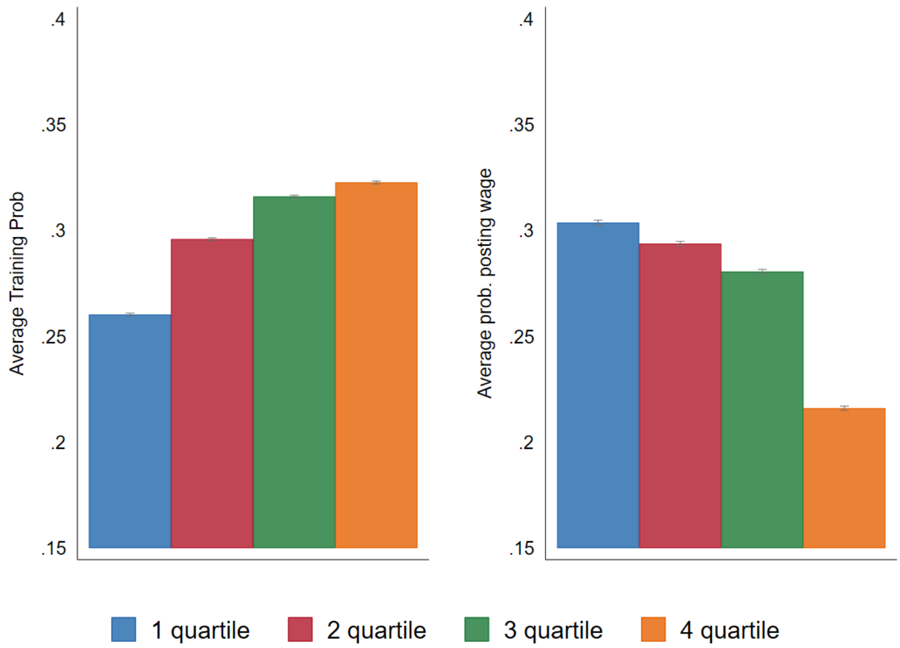
Figure 2.8: On-the-job training offer by education and experience requirements

(a) Education requirement (b) Experience requirement



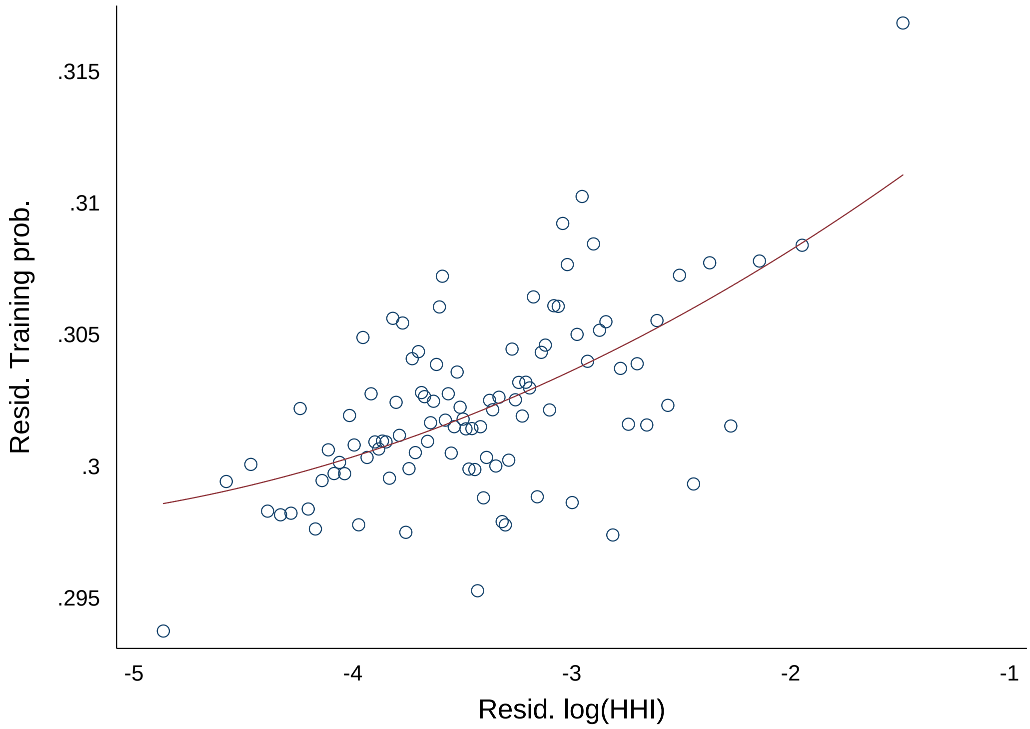
Note: Using BGT 2019 data on our 10% random sample of employers, the Figure plots the probability of offering training according to the level of education (Panel 2.8a) and experience demanded (Panel 2.8b) in the vacancy.

Figure 2.8: Average training offer and wage posted across HHI quartiles



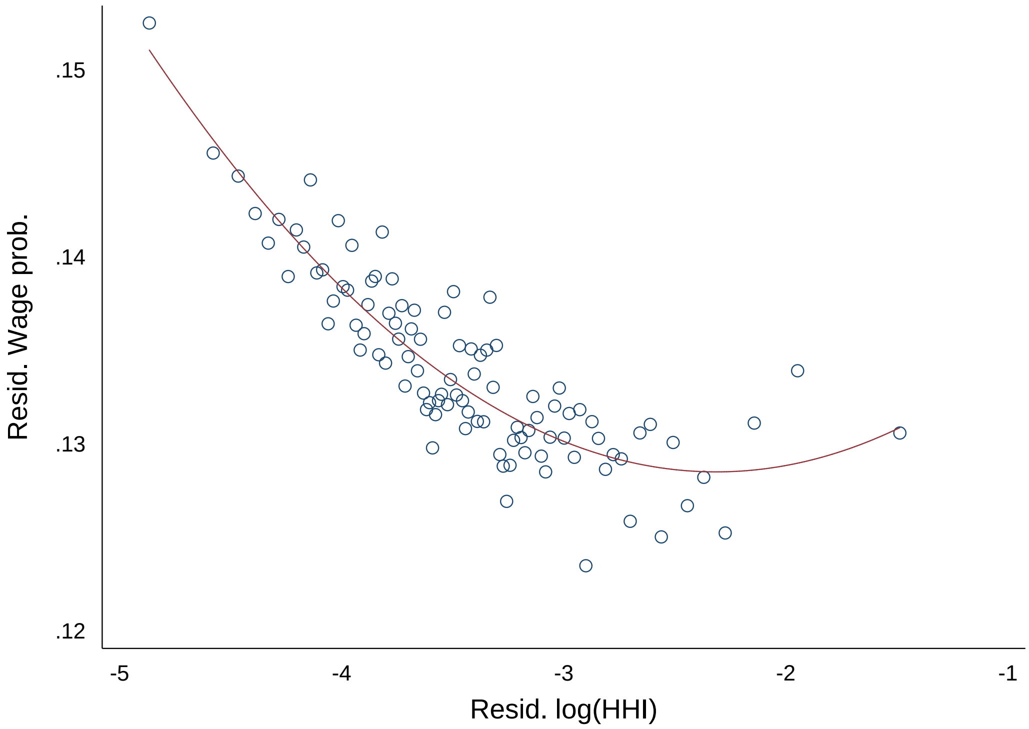
Note: Using BGT 2019 data on our 10% random sample of employers, the Figure (left) shows the average training probability across the HHI distribution quartiles (Q1=0.006, Q2=0.15, Q3=0.48) whereas the (right) Figure displays the share of vacancies posting the wage offered across the different HHI quartiles.

Figure 2.8: Binscatter plot, residualized regression of labor market concentration and training offer



Sample: all vacancies posted between 2013-2019, by a random sample of 10% of all the employers posting vacancy 2019.
Note: The residuals are computed using as regressors SOC 6-dig, MSA, year, sector, employer, education and experience level fixed effects.

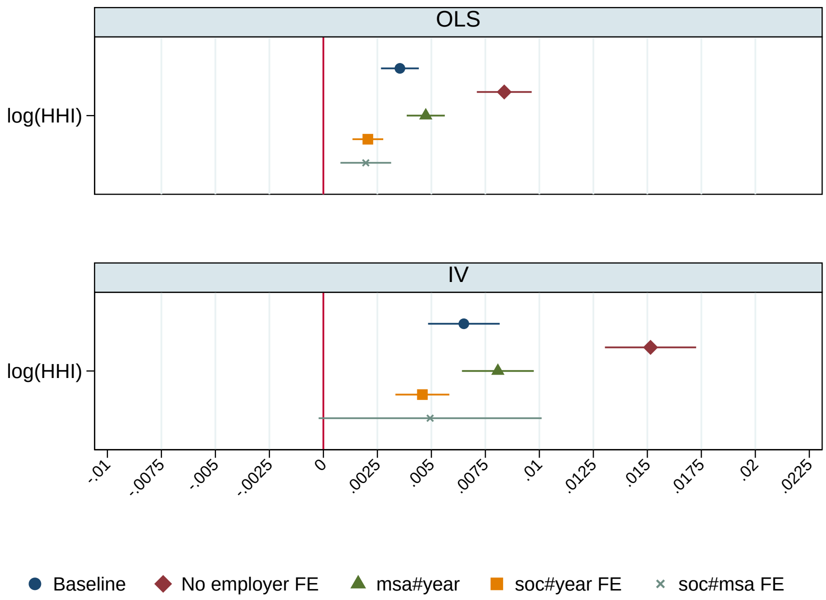
Figure 2.8: Binscatter plot, residualized regression of labor market concentration and wage posted



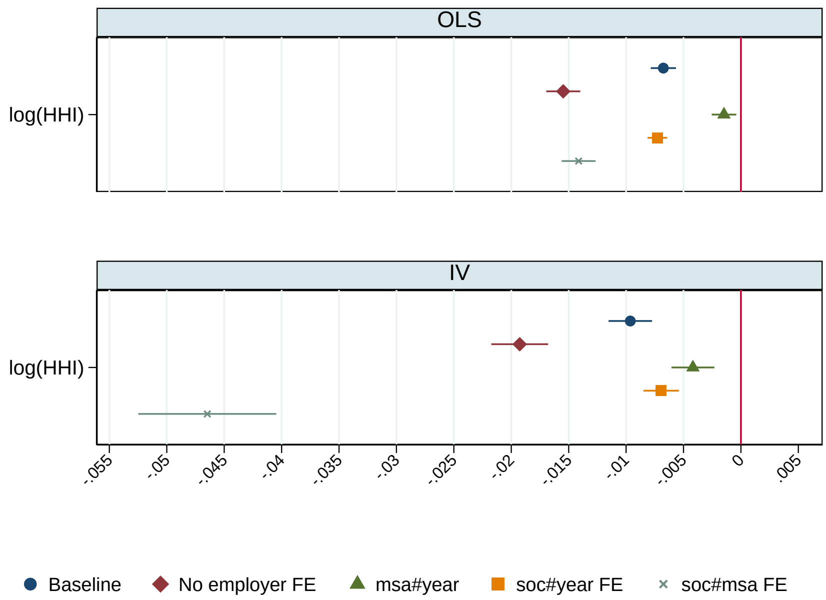
Sample: all vacancies posted between 2013-2019, by a random sample of 10% of all the employers posting vacancy 2019.
Note: The residuals are computed using as regressors SOC 6-dig, MSA, year, sector, employer, education and experience level fixed effects.

Figure 2.8: Coefficients of training and wage on HHI regressions: robustness checks

(a) Training probability



(b) Posted Wage probability



Note: all vacancies posted between 2013-2019, by a random sample of 10% of all the employers posting vacancy 2019. These Figures plot the coefficient of log. HHI on the probability on offering training (Panel 2.8a) and on disclosing wage information (Panel 2.8b). The blue circle shows the estimate when we use individual fixed effects for MSA, year, occupation, sector, and employer. The red diamond uses the same fixed effects of the blue circle one except that it removes the employer fixed effects. The green triangle differs from the baseline has instead of having individual fixed effects for MSA and year, it uses their combination. The yellow square considers the combination of occupation and year, while the teal cross the combination between MSA and occupation. All the regressions controlled for the level of experience and education demanded. Standard errors are clustered at the market level, which consists of the combination between MSA, occupation, and year.

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D Online Appendix

D.1 Tagging process

Figures 2.8 and 2.8 show the tagging instructions given to twelve research assistants in December 2020. We prepare a sample of vacancy posted in 2019. First, we take a random sample of 5,000 vacancies, denoted $\mathcal{S}_a$. The random sampling is stratified per month. Second, we select among the 2019 vacancies all vacancies whose text comprises the words "train", "tuition reimbursement", "personal development plan", "career development", "professional development program", "education assistance", "continuing education". From this subsample, we take a random sample of 5,000 vacancies, denoted $\mathcal{S}_b$, still stratifying per month. We append both samples to obtain the $\mathcal{S}$ sample to be tagged. From this sample of 10,000 vacancies, we ask each Research Assistant to tag 500 vacancies each.

D.2 Alternative approaches to measure labor market competition and comparison with employment concentration

In Section 2.2.2, we compare the Herfindhal-Hirschman index (HHI) with the unemployment rate from Local Area Unemployment Statistics (LAUS) from U.S. Bureau of Labor Statistics and the job creation and job destruction from Business Dynamics Statistics (BDS) from U.S Census.

The LAUS data combines three different sources: the Current Population Survey (CPS), the Current Employment Statistics (CES) survey, and state unemployment insurance (UI) systems, to create estimates that are adjusted to the statewide measures of unemployment.[22]

We use the LAUS annual information on the unemployment rate for each metropolitan

[22] More information and data are available at: https://www.bls.gov/lau/home.htm

Figure 2.8: Tagging instructions: page 1

TAGGING Instructions

Each of the following tags is a binary variable. Write 1 for TRUE and leave it blank for FALSE. Write U if you are unsure.
One job ad can have multiple flags.
For each of the TRUE or Unsure flags, report, in its respective "key phrase" column, the phrase(s)/group of words for which you made that decision.
If there are more phrases referring to a Tag, separate them with a semicolon ";".

TAGS list

- **Y (training)**
  - The job ad offers/sponsors some form of training or education program that will help new hires to acquire new competences or skills
    - *Examples*: "we'll train you"; "Paid training"; "New employee training"; "Training and room to advance"; "Practice-paid continuing education opportunities"; "* Paid Training & Continuous Professional Development"; "8-week comprehensive training program"; "No Experience Needed - Paid Training!"; "continuing education and advancements are among our top priorities"; …

- **G (general training)**
  - If the training/education offered has a general purpose, that can be recognized or transferred to other employers. The training is not limited to some employer's specific competences. In particular, flag those training offers for which a worker will receive some type of certification for the training received.
    - Ex: "Educational Assistance programs"; "Tuition Reimbursement"; "online training courses"; …

- **S (specific training)**
  - If the training is specific to that occupation/employer. The training is intended to provide the job applicants with specific skills/competences required to perform that job for that employer, but it's hardly exploitable by competing firms. For example, training individuals on firm products' features, or training program designed to introduce workers to the company organizational policies or guidelines.
    - Ex: "You'll be trained to educate clients on our products, services, and benefits"; "Brand training are provided before going into the field"; …

***Note:** General and specific training are training, but not all trainings are either generic or specific.*
When the training offer is clearly neither generic nor specific, flag exclusively the Y tag. If it is specific (general), flag both Y and S (G) tags. A single job ad can offers simultaneously general and specific training.

Note:

Figure 2.8: Tagging instructions: page 2

The rationale behind the following last tags is to enable the machine learning algorithm to distinguish job ads that offer "proper" training from those that instead refer to training as a task or requirement demanded to the job candidate.

- **T (task)**
  - Training is not a "benefit" but a task/mansion for the applicants. The job applicants will not receive training, but they are those that will train other employees or clients.
    - "Set up training and mentoring to grow team"; "Train and mentor new team members"; "provide education, training and support to patients and families"; "Conducts field training or retraining and instructs crew on new or revised job units"; …

- **R (requirement)**
  - The employer requires job applicants to possess some sort of training, or the possess of some sort of training is considered a plus. Do not consider demands for previous experience/skill/competence in this flag but consider only those ads where training is explicitly demanded.
    - "Experience in implementation, training and documentation preferred."; "Subspecialty training/certification is also highly desirable but not required"; "should have prior military or law enforcement experience, or comparable training or certification," …

- **D (disclaimer)**
  - The job ad refers to training, however this is not specific to this job ad, but it's included in a generic disclaimer.
    - "This policy applies to all terms and conditions of employment, including recruiting, hiring, placement, promotion, termination, layoff, recall, and transfers, leaves of absence, compensation and training."; "[We use this information for ..] manage workforce activities and personnel generally, including for recruitment, background screening, performance management, career development, payments administration, employee training, leaves and promotions"; ..

- **E (equality & diversity)**
  - The job ad has an explicit statement on equality and diversity in hiring
    - "We are an equal opportunity employer"; "We encourage applications from under-represented groups"…

Note:

Figure 2.8: Example of a False Negative

SWAT Inventory Specialist
Best Buy
Mobile, Alabama

What does a Best Buy SWAT Inventory Specialist do?

At Best Buy our mission is to leverage the unique talents and passions of our employees to inspire, delight, and enrich the lives our customers through technology and all its possibilities. If you have a passion and curiosity for what is possible and enjoy people, we invite you to join us on this mission.

A Best Buy SWAT Inventory Specialist ensures inventory integrity in the store through a variety of inventory adjustments and data collection tools. The SWAT Specialist consistently and accurately completes and communicates stock count. They identify, determine and communicate high shrink categories. After identifying the root cause of replenishment issues, they follow up with leadership until the problem is resolved.

Job responsibilities include:

*Executing the inventory integrity process from end to end
*completing inventory daily tasks as assigned
*communicating and coaching store employees and leadership on the importance of inventory integrity and any process gaps that were identified
*Other duties as assigned.

What are the Professional Requirements of a Best Buy SWAT Inventory Specialist?

Basic Qualifications
*Ability to work successfully as part of a team
*Ability to work a flexible schedule inclusive of holidays, nights and weekends
*Ability to lift or maneuver 50-100 pounds, with or without accommodations
Preferred Qualifications
*3 months experience in retail, customer service or related fields

Additional Job Information
What are my rewards and benefits?
Discover your career here! At Best Buy we offer much more than a paycheck. Surrounded by the latest and greatest technology, a team of amazing coworkers and a work environment where anything is possible, you'll find it easy to be your best when you work with us. We provide an exciting work environment with a community of techno learners where you can be yourself while investing in your career. Empowered with knowledge you will discover endless opportunities to grow. From deep employee discounts to tuition reimbursement, to health, wealth and wellness benefits, to learning and development programs, we believe the success of our company depends on the passion of employees for learning, technology and people.

Figure 2.8: Example of a False Positive

IT Systems Engineer - Federal (N)
Centurylink
WORKS FROM HOME - Colorado, United States
Information Technology

Job Summary:
CenturyLink (NYSE: CTL) is a global communications and IT services company focused on connecting its customers to the power of the digital world CenturyLink offers network and data systems management, big data analytics, managed security services, hosting, cloud, and IT consulting services The company provides broadband, voice, video, advanced data and managed network services over a robust 265,000-route-mile US fiber network and a 360,000-route-mile international transport network Visit CenturyLink for more information
As an integral member of the Tier II group, the IT Systems Engineer II provides advanced Tier II support of a nationwide diverse fiber optic OTN/DWDM transport backbone, as well as two (2) geographically, separated Network Operation Centers (NOC) The position serves as the NOC primary point of contact (POC) for problem escalations to include troubleshooting network devices, tools, and data services The Tier II Engineer will interact with Network Provisioners and/or equipment vendors to identify and develop the solution of escalated troubles The Tier II Engineer is expected to provide accurate documentation such as SOPs, Training Modules, Reports and Project Narratives. The position requires a high-level understanding of Layers 1/2 inter-dependences and Transport proficiency. The network is expected to sustain continual growth to include additional sites and customers across the life of the program and the ITSE responsibilities continue to grow as new customers are added to the network.
Job Description:
-Perform Transport, IP, and Network Management functions in engineering and operations environment and operates as technical lead on problem escalations Serves as the first level of escalation to Tier 1 NOC personnel on Transport related issues
-Serves as technical POC and Lead for Provisioning, Configurations, and TTU Interface with Network Provisioner and configuration managers for requirements, designs, and any other information needed to perform tasks
-Performs advanced diagnostics using software and hardware tools to determine network status and optimize network performance
-Assist provisioning, configurations, and TTU tasks by supporting new system/circuit activations or deactivations as driven by customer requirements
-The ITSE II works closely with Provisioner in implementing system requirements to provide connectivity for TDM (DS-1, DS-3), SONET (OC-12/48/192), OTN, IP, and DWDM paths
-Provide technical guidance, direction, and training to junior technicians with emphasis on Transport equipment
-Create technical operational documentation and SOP for Transport discipline supporting the NOC
-Create and maintain Circuit Layout Records (CLR), Network Diagrams, and other supporting documentation Review and provide feedback or updates to network as-built, Engineering Development Plans (EDP), and configuration management drawings
-On-call after hours/on-call support as required
-Junior Technical to Network Provisioner and ITSE III: receive technical guidance and mentorship
-85% Initial travel is required 13;
Qualifications:
-Bachelor's degree in an Information Technology field and 5 years experience required or seven years of applicable work experience
-The individual is required to keep up with the high demand for the position
-Firm knowledge of SONET, OTN, DWDM, and IP, as well as a high level of proficiency in troubleshooting service troubles in this arena, is required
-Experience with Ciena and Infinera Optical equipment and software is required Long haul optical equipment certifications and training are highly desired
-Demonstrates a high-level of proficiency in IP technical discipline Able to operate and accomplish the technical task with minimum guidance Proficient knowledge of common network architectures for routing, switching, and security technologies are required
-Familiar with the uses of Transport management tool and network management protocols, including but not limited to One-Control, Node Manager, Site Manager
-Security+ or equivalent IAT/IAM/IASAE Level 2 of DoD 85701 is required
-JNCIA or CCNA is preferred
-Firm knowledge of the encryption devices KG-175G/D, KIV-7M, KG-340
Other Requirements
-This position requires a Top Secret/SCI clearance
-Expected to work in a shift environment in support of 24x7 operations
-Up to 15% travel can be expected due to possible deployments to lab facilities and other NOC locations (85% initial on the job travel should be expected) 13;
Requisition:
This job may require successful completion of an online assessment A brief description of the assessments can be viewed on our website at findcenturylinkjobs/testguides/
EEO Statement:
We are committed to providing equal employment opportunities to all persons regardless of race, color, ancestry, citizenship, national origin, religion, veteran status, disability, genetic characteristic or information, age, gender, sexual orientation, gender identity, marital status, family status, pregnancy, or other legally protected status (collectively, protected statuses) We do not tolerate unlawful discrimination in any employment decisions, including recruiting, hiring, compensation, promotion, benefits, discipline, termination, job assignments or training.
Disclaimer:
The above job definition information has been designed to indicate the general nature and level of work performed by employees within this classification It is not designed to contain or be interpreted as a comprehensive inventory of all duties, responsibilities, and qualifications required of employees assigned to this job Job duties and responsibilities are subject to change based on changing business needs and conditions.

statistical area (MSA), however LAUS does not provide additional information on the occupation or industry of these unemployed workers. Therefore, for comparability reason, we average our HHI measure to the MSA × year; as follows

$$HHI_{m,t} = \sum_j \mu_{j,m,t} HHI_{j,m,t}$$

were $\mu_{j,m,t}$ is the share of vacancies posted in MSA m by occupation j in year t, and $HHI_{j,m,t}$ is the aforementioned HHI measured at MSA×SOC×year.

The Business Dynamics Statistics (BDS) is a product of the U.S. Census Bureau, and it is compiled from the Longitudinal Business Database (LBD), a confidential database.

The Business Dynamics Statistics (BDS) tracks changes over time, providing annual measures of establishment openings and closings, firm startups and shutdowns, and job creation and destruction for each establishment. These measures are available at finest dimension as at a combination between an industrial sector, 2-digit NAICS, MSA, and year.[23]

We focus mainly on the job creation and job destruction rate measures. These measure start from job destruction and job creation, which are the number of jobs created or destructed in all the establishment in a specific segment (MSA×NAICS2-dig) each year. These absolute measure are then divided by the average number of employees across establishment in that segment to construct the job creation and destruction rates.

As for the LAUS unemployment measure, also for this measure there is an issue of comparability with our HHI measure, for this reason we average our HHI measure at the same

[23]More information and access to the data at the following link: https://www.census.gov/programs-surveys/bds/data.html

level of the BDS measure, as follows:

$$HHI_{m,k,t} = \sum_j \mu_{jkmt} HHI_{jmt}$$

where μ_{jkmt} is the share of vacancies for occupation j in sector k, for the same MSA m and year t.

E Extra Tables and Figures

E.1 Extra Tables

Table T.2.1: First Stage

	log(HHI)	log(HHI)	log(HHI)
instrument log (HHI)	0.1282***	0.1244***	0.1185***
	(0.0035)	(0.0035)	(0.0032)
Controls-IV	✓	✓	✓
Year FE	✓	✓	✓
MSA FE	✓	✓	✓
SOC_6d FE	✓	✓	✓
NAICS_2d FE		✓	✓
Employer_FE			✓
R^2	0.836	0.828	0.843
N	7,444,415	6,428,522	6,401,726

Table T.2.2: Estimates of labor market concentration on predicted training probability, excluding the years 2018 and 2019

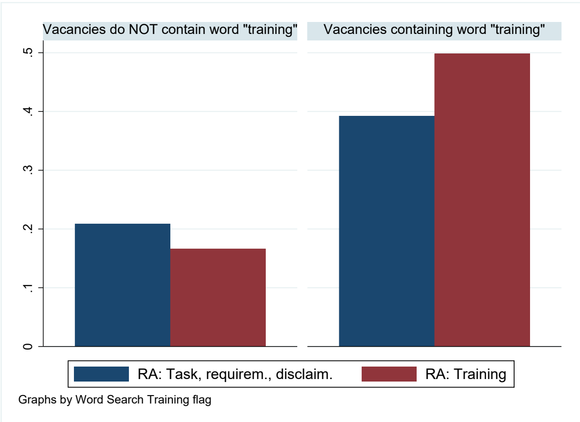
	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
log(HHI)	0.0076***	0.0078***	0.0048***	0.0088***	0.0099***	0.0071***
	(0.0009)	(0.0009)	(0.0006)	(0.0033)	(0.0035)	(0.0027)
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓	✓	✓
SOC_6d FE	✓	✓	✓	✓	✓	✓
NAICS_2d FE		✓	✓		✓	✓
Employer_FE			✓			✓
Controls-IV				✓	✓	✓
MDV	0.291	0.300	0.300	0.282	0.291	0.291
mean(HHI)	0.077	0.080	0.080	0.072	0.074	0.074
std(log(HHI))	1.240	1.231	1.231	1.252	1.244	1.244
R2	.229	.242	.472	.	.	.
F	.	.	.	927	976	1,067
no employers	33,689	28,030	20,216	29,287	24,150	16,879
N	7,081,951	6,514,483	6,506,669	4,499,991	4,115,728	4,108,457

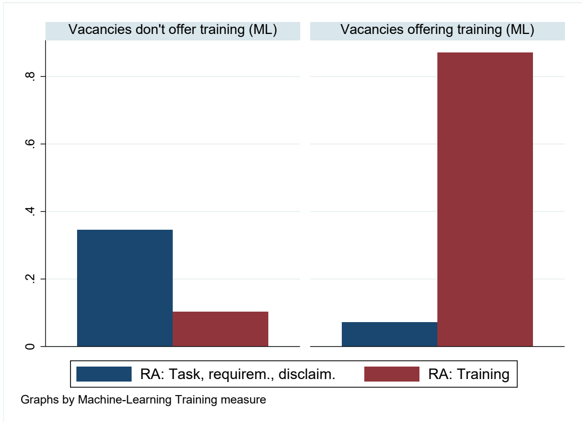
Sample: all vacancies posted between 2013-2017, by a random sample of 10% of all the employers posting vacancy 2019.

Notes: Each observation consists in a vacancy. This table reports the TSLS and OLS regression outputs using as dependent variable *Training*, which defines the estimated probability that that vacancy is offering on-the-job training. The independent variable is the log of the employment HHI, measured at the occupation (6-digit SOC code), Metropolitan Statistical Area (MSA), and year level. The "Control-IV" identifies the exposure, vacancy growth, and predicted vacancy growth controls as described in Section 2.5. MDV reports the Mean of the Dependent Variable. F shows the Kleibergen-Paap F Statistics from the regression. Standard errors are clustered at the market level, which consists of the combination between MSA, occupation, and year. ***, **, and * indicate significance level at the 1%, 5%, and 10% level, respectively.

E.2 Extra Figures

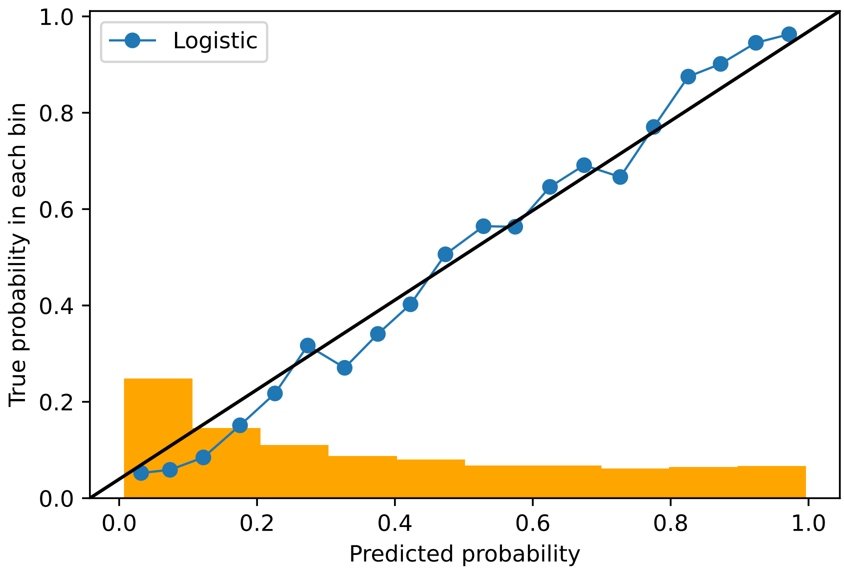
Figure F.2.2: Comparison between Machine learning and Word search approaches





Notes: Figures compare the share of correct predictions using our machine learning algorithm (ML) and searching for the word "training" within a job vacancy text. Using the manual annotations, in blues are indicated those vacancies that requires training as a requirement or task, or mention training in a disclaimer. In red those vacancies that actually offer training.

Figure F.2.2: Calibration Plot for Training classifier

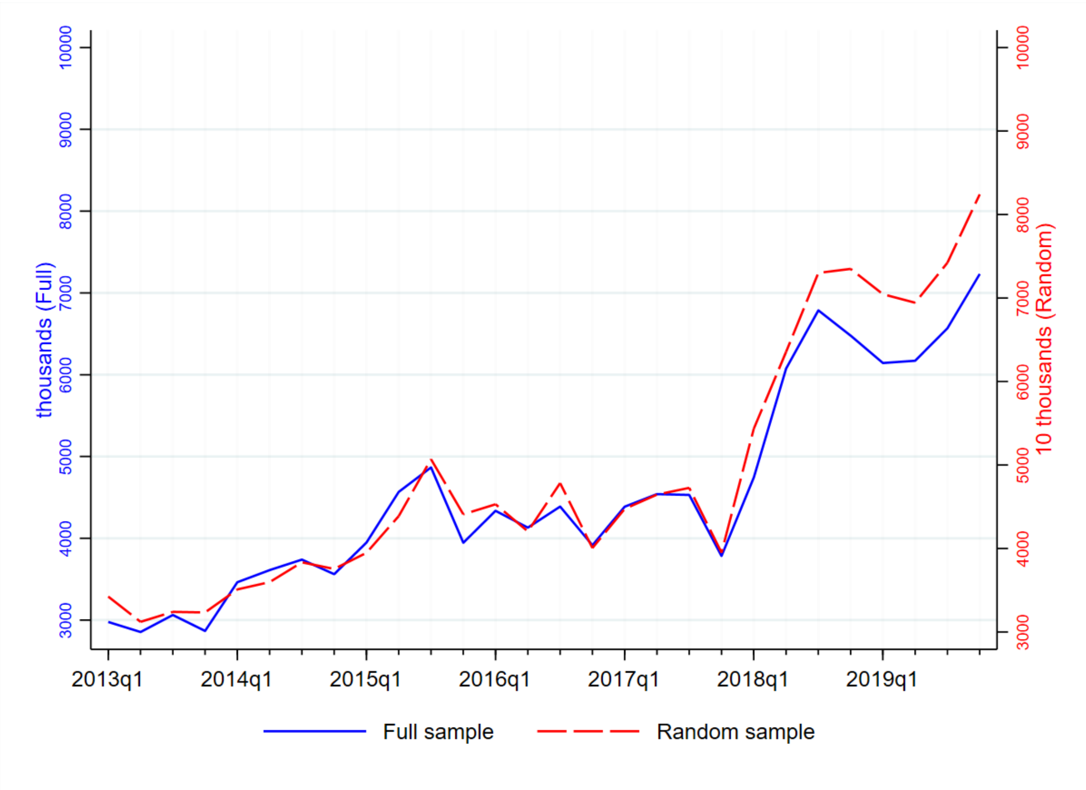


Notes: Calibration plot showing the average true training offers probability (on the y-axis) and the average predicted training probability (x-axis) for each of the 20 bins in which the (out-of-sample) test set is divided according to the predicted training probability. The orange histogram displays the density of the predicted training probability. The 45-degree line identifies perfect calibration.

Figure F.2.2: Word Cloud: most predictive phrases for offering training

Notes: The Figure displays the most predictive n-grams to identifies vacancies offering on-the-job training.

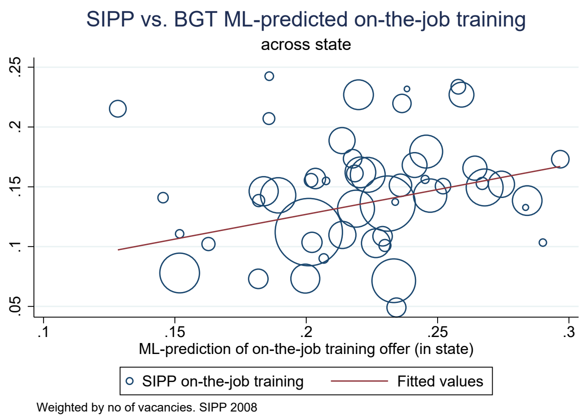
Figure F.2.2: Number of job ads: Full sample vs Random sample



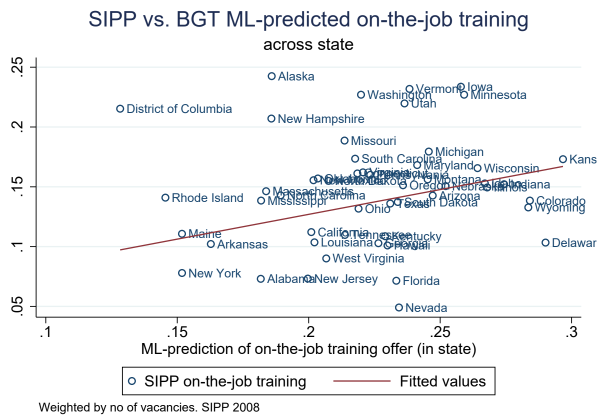
Note: This Figure plots time series evolution of the quarterly number of vacancies in the entire BGT data excluding those vacancies with no employer name and our random sample consisting of all the vacancies posted by 10% of the employers posting vacancies in 2019. The quarterly number of vacancies are expressed in thousands of units.

Figure F.2.2: Comparison btw BLS, SIPP and BGT measures of on-the-training

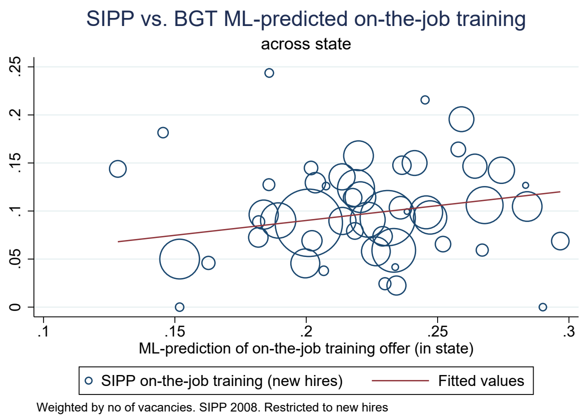
(a) US states



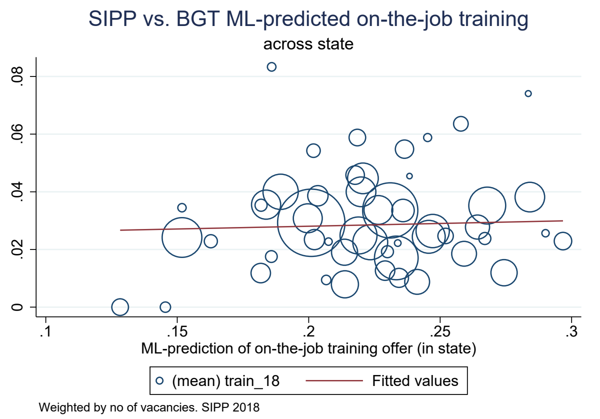
(b) US states



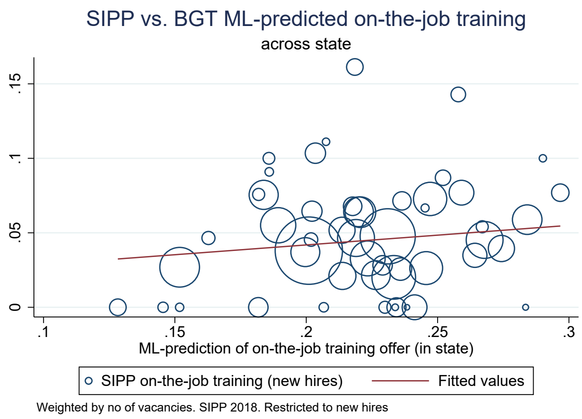
(c) US states



(d) US states

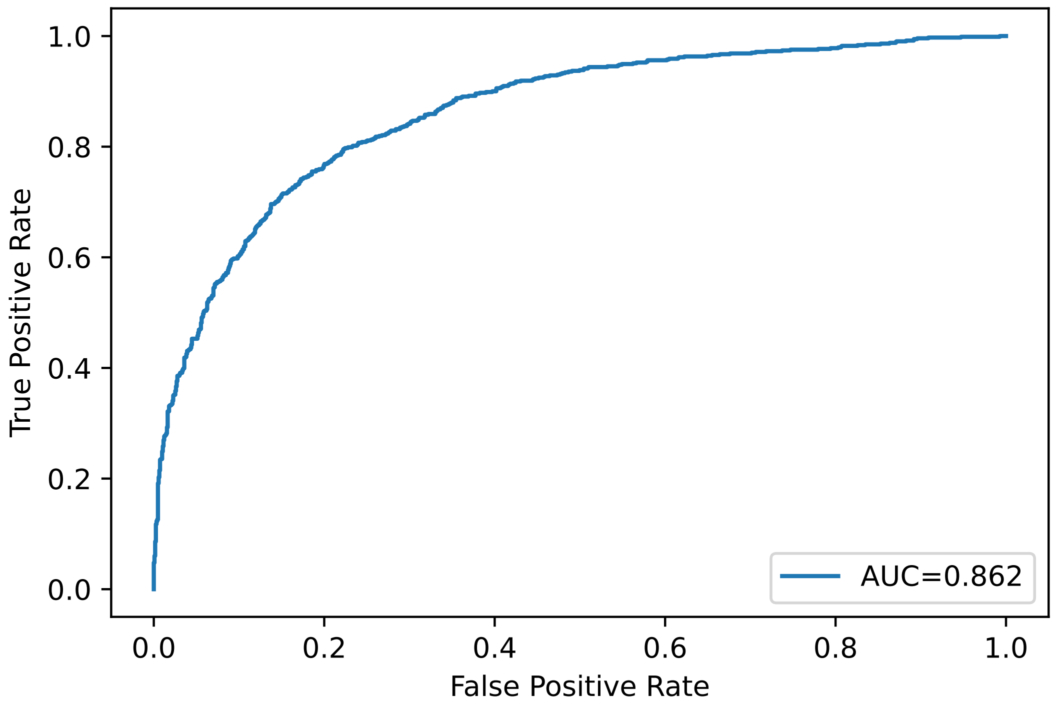


(e) US states



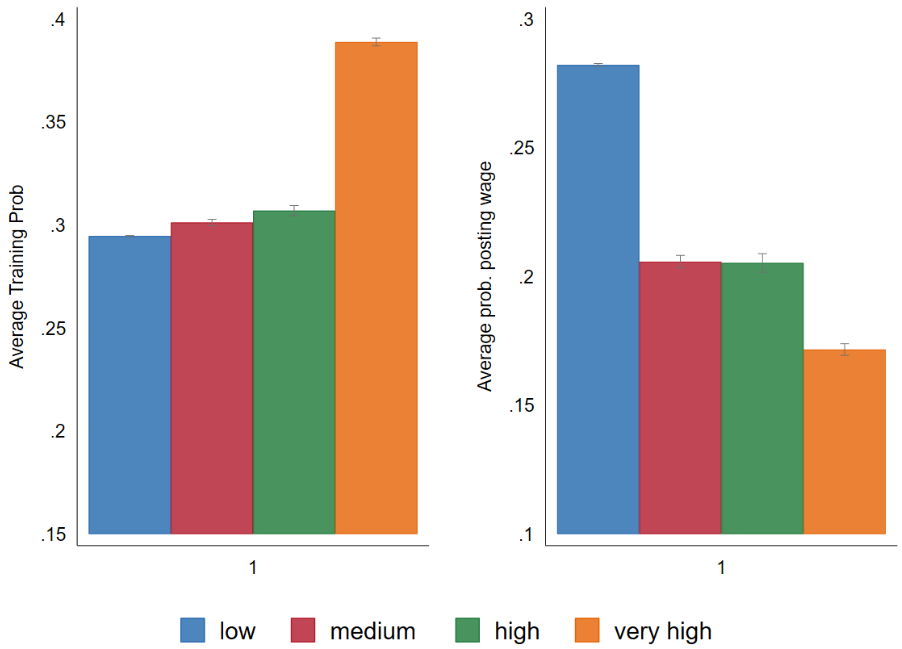
Note: This Figure compares various on-the-job training measures. Our new measure obtained from BGT job ads is on the X axis, while Panels have the SIPP measure on the y-axis. We look at the correlation across states. Weighted by the number of job ads posted in 2019.

Figure F.2.2: AUC-ROC graph



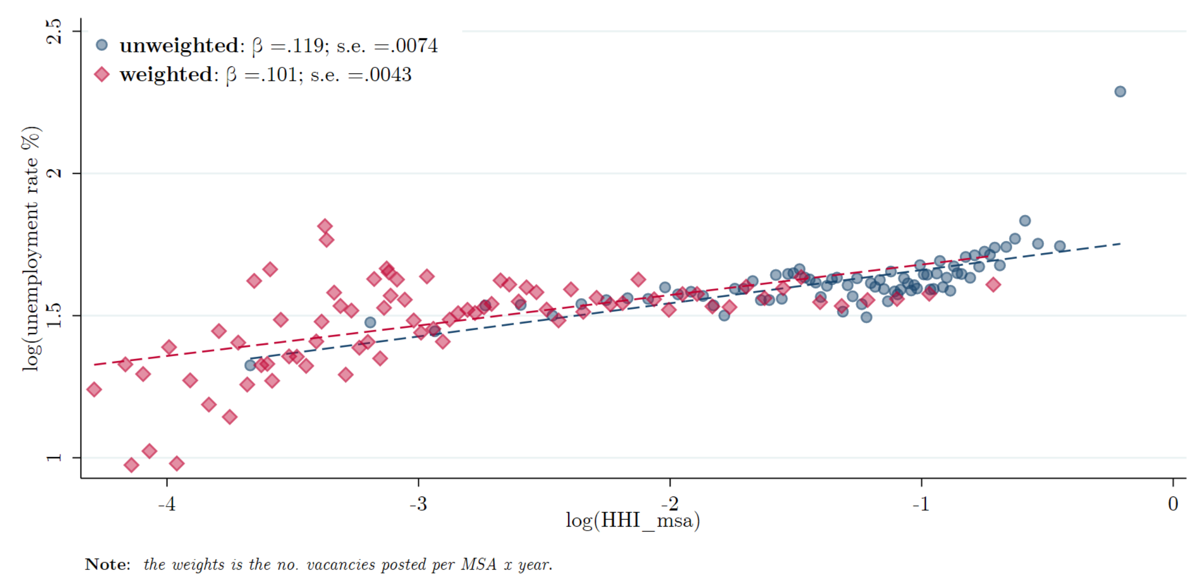
Note: The figure plots ROC curve and the AUC measure of the Logistic regression classifier for predicting training offers. The ROC (Receiver Operating Characteristic) Curve displays the percentage of true positives predicted by the model as the prediction probability cutoff is lowered from 1 to 0. The higher the AUC (area under the curve), the more accurately our model is able to predict outcomes. The True positive rate is defined as TP/(TP+FN), while the False Positive rate as FP/(TN+FP). A AUC of 0.86 means that that given a randomly-seleted training-offering vacancy and a non-training-offering vacancy, there is a 86% change that our model ranks correctly the training vacancy with more predicted probability than the non-training one.

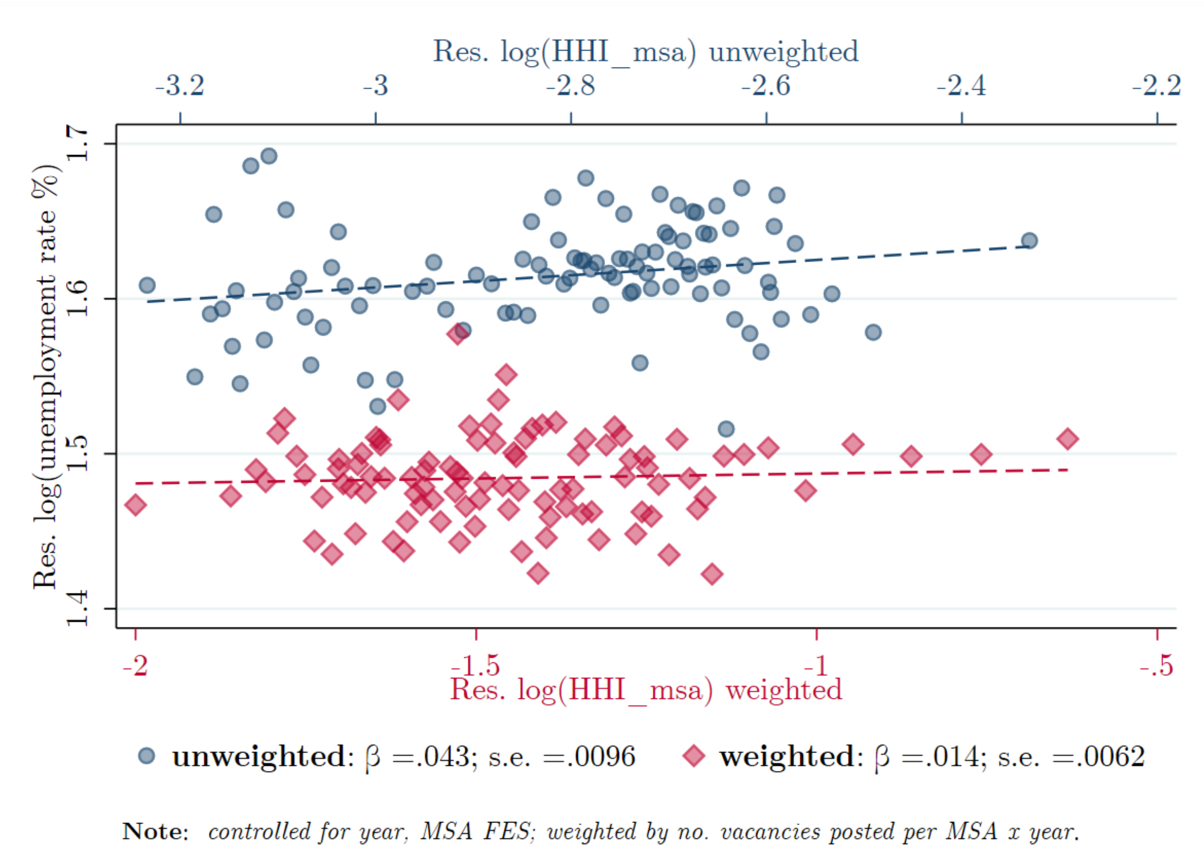
Figure F.2.2: Average training offer and wage posted across HHI classes



Note: Using BGT 2019 data on our 10% random sample of employers, the Figure (left) shows the average training probability across different HHI groups following **(alias?)** categories, whereas the (right) Figure displays the share of vacancies posting the wage offered across the different HHI groups.

Figure F.2.2: Binned scatter plots: Log. unemployment rate and HHI_MSA





Note: Binned scatter plots between the LAUS unemployemnt rate and log HHI_MSA, for the years 2013-2019. An observation is a combination between a year, and MSA. Weighted by the number of vacancies posted in a MSA × year.

Chapter 3

Skill demand and employer concentration: evidence from vacancy text

This chapter is based on joint work with Emilio Colombo

3.1 Introduction

In recent years a great deal of emphasis has been placed on the rise in market concentration (Covarrubias et al., 2019; Grullon et al., 2019). Increasing concentration is a general phenomenon that can have relevant macroeconomic consequences such as the fall in the labor share (Autor et al., 2020; De Loecker et al., 2020) and the stagnation of aggregate investment (Gutiérrez and Philippon, 2017). In the labor market concentration translates into firms' monopsony power which is often associated with lower wages (larger markdowns), inefficient labor allocation and consequent welfare losses (Marinescu et al., 2021; Azar et al., 2020a; Arnold, 2020; Schubert et al., 2020; Berger et al., 2019; Jarosch et al., 2019; Benmelech et al., 2018).

Another prominent phenomenon observed in labor markets is the change in skill requirement with the increasing relevance and emphasis placed on cognitive and social skills (Modestino et al., 2020; Clemens et al., 2020; Ziegler, 2020; Burke et al., 2019; Kuhn et al., 2018; Deming and Kahn, 2018; Deming, 2017; Beaudry et al., 2016). The literature has mostly associated changes in skill requirements to globalization and technical progress. Yet, little is known about whether and to what extent local labor market concentration *per se* affects skill demand. In this paper we address this question using a unique dataset of Italian Online Job Advertisements which provide granular information on the demand for skills and competencies for detailed occupations and local labor market.

We show that employers in a highly concentrated labor market demand competencies associated with the ability of workers to learn faster (e.g., Social skills) rather than actual knowledge. They also require less experience but higher education. These results are consistent with the hypothesis that employers in more concentrated labor markets are more prone to train their employees. Instead of looking for workers who already have job-specific skills, they look for workers who can acquire them faster and efficiently. Our findings, thus, highlight the importance of tailoring active labor market policies to the specificity of each local labor market.

Our paper innovates on the literature in a number of ways. First we provide evidence of local labor market concentration in Italy. As stressed below, the literature so far has been focused on the US while less evidence so far has been collected on labor market concentration in Europe. Second we provide evidence of skills demand at local level using a detailed skill taxonomy that goes beyond the classical distinction between high and low skills. Third and most importantly, we provide evidence of the relationship between skill demand and labor market concentration. To the best of our knowledge a similar issue has been explored only by Modestino et al. (2020), who, however, focuses exclusively on the level of education and experience demanded. By analyzing detailed skills and competencies we take one step beyond in understanding the features of labor demand in monopsonistic markets. Our results have clear implications for HR management practices as they show that the recruitment behavior and the demand for skills differ in monopsonistic markets.[1]

Our explanation of the relationship between labor market concentration and skill demand is therefore based on a training rationale. To provide the intuition, assume that workers are characterized by two sets of skills: one more challenging to learn (e.g., soft skills) and the other easier to teach and learn, such as standard technical competencies (e.g. a specific software). Assume that those two sets of skills are equally important for production. However the second set of skills, being easier to be taught, can be provided to the workers through on-the-job training more efficiently (i.e. at a lower cost). Therefore, firm's training decision impacts on the demand for skills as some are more "trainable" than others. If firms with higher market power face higher recruitment costs, they are also more likely to invest in training, providing internally trainable skills while looking on the market for un-trainable skills. Therefore firms will look for skills that are relatively difficult to be taught or that help new workers acquire new competencies fast and effectively.

The remainder of the paper is structured as follows. Section 3.2 illustrates the literature most closely related with the paper; section 3.3 develops a simple theoretical setting that conveys the main testable hypothesis; section 3.4 presents the data and the methodology; section 3.5 describes the empirical strategy; section 3.6 illustrates the results, section 3.7 provides some robustness checks, finally section 3.8 concludes.

[1] Indeed the US Antitrust Guidance for Human Resource Professionals **(alias?)** has been issued to draw attention to the effect that labor market concentration and anticompetitive practices affecting human resources.

3.2 Related literature

Our paper is related to two major strands of the literature. The first is the analysis of labor market concentration and its effects on firms' training decisions. There is strong evidence of increasing concentration in US labor market (Hershbein et al., 2021; Azar et al., 2020a; Berger et al., 2019), and there is also a growing evidence of the same effect in Europe (in addition to our paper and Marcato (2021) for Italy, see Marinescu et al. (2021) for France and Bighelli et al. (2021) for Europe). The literature shows that stronger monopsony power allows firms to extract large rents from workers' productivity.[2] So long as on the job training increases workers' performance, it is more likely to be provided by firms' with considerable market power. Empirically the link between market structure and firms' training decision is well documented. For example, Rzepka and Tamm (2016); Brunello and Gambarotto (2007); Brunello and De Paola (2008); Harhoff and Kane (1997) find a negative and significant effect of labor market competition on firms' decision to train.[3]

The second strand of the literature is the analysis of skill demand. Since the seminal paper by Autor et al. (2003) the "task approach" has been used to analyze the changing structure of labor demand in industrialized countries. According to this approach the fundamental units of production are job tasks, which are then combined to produce output. Tasks in turn can be performed by capital, foreign or domestic labor, and by different types of labor; in equilibrium the assignment of factors to tasks is determined by comparative advantages.[4] The task approach has been successfully used to investigate how and to what extent technological progress and globalization (outsourcing and offshoring) change labor demand, however when coming to skill demand the analysis has been limited to the

[2]See, among others, Acemoglu and Pischke (1998, 1999); Stevens (1994); Manning (2003); Moen and Rosén (2004); Manning (2021); Sokolova and Sorensen (2021)

[3]See also Bratti et al. (2021); Marcato (2021); Starr (2019); Muehlemann and Wolter (2011); Picchio and Van Ours (2011) for similar analysis.

[4]See Acemoglu and Autor (2011) for a review.

distinction between high and low skills or between routine and non routine tasks. The reason lies in the difficulty of measuring tasks and the skills associated with them. One approach has focused on occupational job descriptor databases such as the U.S. Dictionary of Occupational Titles; however the infrequent updates of such data-sets made them useful only for low frequency long run analysis (see Lin (2011) and Deming (2017)). Other approaches are based on surveys such as the IAB/BIBB in Germany, the ICP survey in Italy (Cirillo et al., 2021), the UK skill survey or the STAMP survey in the US. The limit of surveys however is that they are top-down tools which need to be designed first and subsequently implemented. For this reason, due also to the burden on the respondent, questions about skills are restricted to a general pre-defined list. Recently a new impulse to this literature has been provided by the availability of detailed data from Online Job Advertisements. These can provide information about detailed skill requirements for each occupation. Such data has been used mainly in the US (Azar et al., 2020b; Deming and Kahn, 2018; Hershbein and Kahn, 2018; Modestino et al., 2016, 2020) while little information is available in Europe with the exception of Colombo et al. (2019) for Italy and Adrjan and Lydon (2019) for Ireland. Our paper contributes to this literature by providing detailed evidence of skill needs in the Italian local labor market. The analysis of online job advertisements has a number of advantages for the extracting information about skills. First it follows a bottom-up approach that is entirely data-driven. The initial data collected contains all the information that individual firms post on the web. This large amount of data is subsequently filtered and processed using appropriate techniques to obtain the required information. In this way the tools help to categorize a pre-existing information set, but they do not pre-classify the information itself (as generally done in surveys). This is particularly useful for the identification of soft skills and certain occupation-specific skills that surveys often ignore. In our data we are able to identify more than 250 specific skills that can be subsequently grouped in different macro categories following a standard taxonomy.

3.3 Theoretical Framework

Although the main focus of our paper is empirical, to guide the empirical analysis, we present a theoretical setting that is able to deliver simple testable predictions. In this section we discuss the main implications and the intuition of the model. The detailed derivations are reported in the Appendix. Our model encompasses two different approaches. First we present a generalised monoposnistic model (section 3.3.1) that shows how market concentration affects firms' recruitment decisions. Second we nest the first model in a standard task model (section 3.3.2) where firms can choose between trainable and untrainable labor inputs.

3.3.1 Generalised monopsonistic model

Following Manning (2006), we consider a monopsonistic model where firms compete for workers, but where, in order to set their level of employment N, they must pay both a direct and an indirect cost. The direct cost per worker is the wage W, whereas the indirect cost, $I(N)$, can be thought as the recruiting cost necessary to substitute the exogeneously separated workers with new recruits. We assume that this recruiting cost is increasing with the share of employment working in the firm, therefore, aggregating at the market level, higher level of concentration leads to higher recruiting costs. The rationale is that the larger is the share of workers working for a firm in a market, the more difficult it becomes to find a good match among potential recruits. Alternatively, one can think that workers have idiosyncratic preference or specific bundle of competencies for a workplace, therefore the larger is the share of employees working in a firm, the costlier it becomes to convince the remaining workers to work in that workplace, because they are those with the lowest idiosyncratic preference or the lack of necessary competencies. The crucial aspect is that employment share drives an increase in hiring costs, rather than the absolute number of employees.[5]

In this setting, a firm chooses N to maximize profits which are given by:

$$\pi = \max_{N} Y(N) - \underbrace{[I(N) - W]}_{C(W,N)} N \tag{3.1}$$

In equation (3.1) the level of employment N affects both the direct cost (through wages) and the indirect cost. The latter effect operates through local labor market concentration: the larger is the firm the larger is its share in the local market, the more concentrated the market is.

The first order condition of equation (3.1) is the following

$$MP_N = (1 + \frac{\partial C(W,N)}{\partial N}\frac{N}{C})C(W,N) = (1 + e(N))C(W,N) \tag{3.2}$$

where MP_N is the marginal productivity of labor and $e(N)$ is the inverse labor supply elasticity which depends on the employment share. As stated above we assume that the inverse labor supply elasticity is increasing with the level of employment, $C'_N > 0$ and $C''_{NN} \geq 0$, which implies that it becomes increasingly costly to recruit workers.[6]

Building on this result, we will proxy the increase in labor market concentration with an increase in the indirect cost of labor through an increase in the employment share, keeping unchanged the level of employment and thus the direct cost.

[5]For a clarifying example, employing ten workers in a very populated market with thousands of workers is different than employing the same number of workers in a small market with dozen employees. In the former, the ten employees firm is a minor actor, while it is a dominant one in the latter. For a more structured framework on how employment share impacts labor supply elasticity and, in turn, hiring costs, see Berger et al. (2019).

[6]In the Appendix, we provide the solution for a simple case when the cost function is linear both in wages and employment share.

The assumption that firms can just adjust their labor force and not their wages is specific for a country with high wage rigidities and collective contracts, like Italy. Although the incentive to reduce wages from the reduction in labor market competition, the downward wage rigidity forbid them this channel, pushing them to intervene through the labor demand one.[7]

3.3.2 Production function

We embed the approach outlined above in a canonical model of human capital with different tasks and factor-augmenting technology (Acemoglu, 2002; Autor et al., 2003; Acemoglu and Autor, 2011). Consider an economy where labor is the only input, divided in two distinct categories: "trainable" and "un-trainable". The competencies in the trainable category can be quickly learned through on-the-job training — for example, standard technical skills. Instead, the "untrainable" category includes those competencies that are difficult to learn because they are linked to character or attitude. Some straightforward examples are competencies like leadership, problem-solving, and social skills. The two groups of skills are both needed for the production. Thus, they are complements and not substitutes.[8]

Assume that production function is a Cobb-Douglas function nested in a constant elasticity of substitution (CES) function:

$$Y = \left[\left(A^{\alpha} T^{1-\alpha} \right)^{\frac{\theta-1}{\theta}} + U^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \tag{3.3}$$

[7]On the wage rigidity in Italy, see for example (Belloc et al., 2019; Boeri et al., 2021). In France, which has a similar framework of Italy, Bassanini et al. (2020) and Marinescu et al. (2021) found a limited effect of concentration on wages, while a strong effects on the number of hirings, supporting our idea that in labor market characterized by high wage rigidity, the employers intervene more through their labor demand rather than their wages.

[8]This distinction of competencies between trainable and untrainable is a convenient simplification. One could easily extend it to a world with a continuum of different groups of competencies, each one with a different cost to be taught.

where T is the trainable labor component, U is the untrainable one, A is the amount of training provided, and $\theta \in [0, \infty)$ is the elasticity of substitution between trainable and untrainable labor inputs. Given that the two skill groups are complements, $0 < \theta < 1$. As an additional simplification, we assume that training can only improve the productivity of the "trainable" labor component.[9]

3.3.3 Equilibrium and empirical predictions

There is a training cost τ linear in the amount of training. Both inputs belong to the same market which follows the structure described in section 3.3.1. Both inputs have the same direct cost W and indirect cost $I(N)$, which depends on the total amount of labor inputs used $N = T + U$.[10] Thus, the profit maximization problem can be written as:

$$\max_{A,T,U} \left[\left(A^{\alpha} T^{1-\alpha} \right)^{\frac{\theta-1}{\theta}} + U^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} - \tau A - C(W, N)N \tag{3.4}$$

where A is the amount of on-the-job training provided. Taking into account that T and U labor inputs have the same increasing cost due to the indirect cost, an employer decides the optimal bundle of untrainable and trainable skills and the total amount of training provided to the latter.

Our main goal is to understand how employment concentration affects employers' demand of trainable vs untrainable labor component. Assume that a rise in employment concen-

[9] An extension of our framework to include a factor-augmenting technology also for the untrainable component would leave the qualitative empirical implication unaffected if the untrainable-augmenting technology has a lower return to scale or a higher cost. To simplify the computation, we also assume constant return to scale between the training and the training labor component, however all the results of interest hold with any function $(A^{\alpha} T^{\beta})$.

[10] This framework could be extended to include separate markets for each of the inputs. However, this extension goes beyond the scope of this paper because the intuition would be less sharp as we would need to take into account relative prices between different inputs. Indeed, the empirical predictions will remain qualitatively unaffected if an increase in concentration will lead to a rise in both indirect input costs. Besides in Italy the existence of national collective contracts, substantially reduces the extent of wage differentiation.

tration increases the indirect cost of both inputs. Given the possibility of improving the productivity of one of the inputs through training, the optimal bundle of factors will depend not only on their relative cost and productivity but also on the ability to substitute the trainable input with training. This option becomes increasingly more profitable as the input costs increase following a rise in market concentration.

Proposition 1. *Consider a general monopsonistic model where employers face an increasing labor cost function, and can choose a bundle of trainable and untrainable labor input as well as the amount of on-the-job training. The ratio between trainable and untrainable inputs decreases with the level of concentration. Formally,*

$$\frac{\partial(T^*/U^*)}{\partial HHI} < 0$$

Therefore employers facing a concentrated labor market are more likely to demand relatively more untrainable competencies. As the concentration rises, the inverse labor supply becomes steeper, increasing the marginal cost of the labor inputs; given that the two inputs are complements, an employer will find it more profitable to divert part of the investment from the trainable input to the untrainable one, substituting the former with an increase in the training investment. Indeed, as a corollary, it can be shown that this simple model also predicts an increase in training spending following an increase in employment concentration.

3.4 Data and measures

3.4.1 Sources

The source of the vacancy data is Wollybi,[11] a project that collects online vacancies in Italy from job portals since February 2013. For internal data consistency, we concentrate on the years from 2015 to 2018, and we select only primary sources, neglecting secondary sources such as aggregators (e.g. websites that re-post vacancies retrieved from other websites).[12] Each vacancy includes detailed information such as location, industry, education, and skill requirements.[13]

To measure the level of concentration across local labor markets, we exploit the Italian ORBIS dataset, AIDA (Analisi Informatizzata Delle Aziende), by Bureau van Dijk, from 2013 to 2018. This dataset contains the full balance sheets and income statements of Italian firms. Similar data have been used in recent research, see for example Kalemli-Ozcan et al. (2015) and Gopinath et al. (2017).

One potential drawback of online vacancies is that they capture only vacancies posted on the Internet and may not be representative of the universe of vacancies. Online vacancies have been used by other papers and have been found fairly representative of the universe of job openings (Hershbein and Kahn, 2018; Modestino et al., 2020). Regarding in particular the Italian case Lovaglio et al. (2020) show that online vacancies display the same time series behaviour of vacancies obtained from official statistics, both overall and at sectoral level. In the appendix we provide a more detailed assessment of the representativeness of online data. Moreover it is worth mentioning that our paper focuses on the

[11] See www.wollybi.com. This source is now part of product of Burning Glass Europe, the European division of Burning Glass Technology.

[12] The sources are all private as the website of the Italian PES at present contains too few vacancies and is rarely updated.

[13] For recent applications and more details on extraction and classification of information from online job advertisements see Colombo et al. (2019).

skill distribution within occupation across markets characterized by different degrees of concentration, therefore any bias that online vacancies may have is likely to be greatly weakened.

3.4.2 Skill classification

A major research challenge pertains the classification of terms extracted from web vacancies into specific taxonomies. While this is easy for occupations, sectors, regions and education as there are well known benchmark taxonomies (respectively ISCO, NACE, NUTS, ISCED), the same does not hold for skills as there is not a standard taxonomy to be used as benchmark. In this work we have used the taxonomy contained in O*NET, developed by the Bureau of labor Statistics.[14] This allows comparability with other papers in the literature most of which follow the O*NET taxonomy. Skills extracted from OJA are classified into the finest level of the O*NET taxonomy which is organised into three hierarchical levels. We used the finest level as building block to construct two classifications. The first is the broadest O*NET level composed of the following categories: *Knowledge*, *Skills*, *Abilities*, *Work Activities*, and *Work Styles*.[15] The broad classification available in O*NET however does not lend itself to a clear interpretation as there are subtle differences between what is classified as skill and what is classified as, say, ability or work activity. For example "mathematical reasoning" is classified as an ability under the category of "cognitive abilities"; on the other hand "use of mathematics to solve problems" is classified as a skill under the category of "basic skills". Moreover "developing and building teams" is considered as a work activity under the category of "interacting with others" while "persuasion" and "coordination" are considered as skills (social skills). Starting from the fines level we have therefore constructed a different skill classification composed of the following groups *Cognitive*, *Social*, *Digital*, *Hard (technical)*, *Organiza-*

[14] www.onetonline.org

[15] The O*NET taxonomy includes also the following broad categories: work context and interests. We excluded the items falling into these categories as they are not useful for our analysis.

tional skills. We did not regroup items of the *Knowledge* category leaving them separate as we believe that the these refer to set of principles and facts applying in generals domains which can be easily linked to the educational system. Table T.3.1 lists the competency classifications and the corresponding description of each category.

3.4.3 Measuring skill intensity

Once extracted the information from vacancies and mapped it into a skill taxonomy the final challenge pertains the creation of measures of intensity of a given skill (or category of skills). Given these categorizations, we define the intensity of the demand for each category with two different measures: a binary and our preferred measure the *term frequency–inverse document frequency* (tf-idf), which is similar to the local-quotient measure used by Alabdulkareem et al. (2018). The binary measure describes whether a vacancy demands at least one skill of that category. In contrast, the *term frequency-inverse document frequency* (tf-idf) documents how important a particular skill is for a vacancy relative to the importance of that skill in the vacancy's occupation.

For a skill category j in vacancy i for occupation o, the *term frequency* (tf_{ijo}) is the share of skills of category j demanded. The *inverse document frequency* (idf_{ijo}) is the log of the share of vacancies in occupation o demanding at least a competency of the category j. Formally, the tf-idf is computed as:

$$tf\text{-}idf_{ijo} = \frac{S_{ijo}}{\sum_j S_{ijo}} \log\left(\frac{\sum_j V_{oj}}{V_{oj}}\right)$$

where S_{ijo} is the number of skills demanded in vacancy i of category j in occupation o; and V_{jo} is the number of vacancies in occupation o demanding a competency of category j.

The tf-idf is a standard measure in the literature of information retrieval[16] and is our preferred measure as it gives more important to occupation specific skills rather than to general skills. Indeed, skill categories that are unimportant for a vacancy will have a low tf-idf score because the tf_{ijo} will be low. On the other hand, very common skill categories will instead have a low tf-idf score because that category will be demanded in most of the vacancies in that occupation; thus, the idf_{ijo} will be very low. On the opposite, specific skills in high demand for a given occupation will be characterised by a high tf-idf score.

Figure F.3.13 shows the distribution of the number of skills demanded for each job ad. We can see that almost half of the vacancies demand less than 5 skills. Figure F.3.13 displays the average number of skills demanded by each group. The categories *Skill*, *Activity*, and *Knowledge* are the most requested with an average of more than two competencies belonging to these categories per job ad. Tables T.3.1 and T.3.2 report the correlation matrices between the different categories for the two different intensity measures.

3.4.4 Measuring labor Market Concentration

Following the literature, we define a local labor market as the combination between a province,[17] an industry/sector, and a year. As measure of concentration we use the Herfindahl-Hirschman Index (HHI), defined as the sum of squares of each firm's employment shares in a local labor market. Figure F.3.13 shows the logarithmic distribution of the HHI at the local labor market level. We find that the average local labor market is moderately concentrated, with a mode around log(HHI) = 7, equivalent to an HHI of 0.11 or an Inverse Herfindahl-Hirschman Index (IHHI) of 9.2.[18] The Inverse Herfindahl-

[16]See Baeza-Yates and Ribeiro-Neto (2011) for a reference.

[17]A province in Italy is equivalent to a NUTS-3 European level classification of regions. Nuts-1 define countries, Nuts-2 regions within countries, Nuts-3 define portions of regions (provinces).

[18]Note that as a standard procedure we have taken the log of the HHI multiplied by 10 000, this is to avoid having negative numbers. To have a sense of these number notice that, according to the guidelines of the US Department of Justice **(alias?)**, a value of HHI above 1500 is "moderately concentrated", and above 2500 is "highly concentrated".

Hirschman Index (IHHI) can be interpreted as the number of equal-sized firms that will induce the same observed HHI.[19]

3.5 Empirical Strategy

For our empirical specification we regress the two measures of skill demand at the vacancy-level on the log-HHI index of the local labor market market where the vacancy was posted, formally

$$Y_{i,pst} = \alpha_p + \alpha_s + \alpha_t + \alpha_o + \beta \log(HHI_{pst}) + \varepsilon_{i,pst}$$

where i denotes the vacancy, p is the province, s is the industry sector, t is the year, and $\log(HHI_{pst})$ is the log of the HHI index for the local labor market (pst). Y is one of the two different competency demand measure, previously described. The α defines the year, industry, province, and occupation fixed effects.[20]

Although our time horizon is short, a possible threat to identify the skill demand effect in our OLS regression is the possible existence of a time-varying market-specific variable that we do not control for, correlated both with the HHI and the skill demand. To further address this issue and provide more robust results, in section 3.7 we use the so-called Hausman-Nevo instrument (see Hausman (1996) and Nevo (2001)). Specifically, we instrument the HHI for each province-industry-year combination with the average of the log of the inverse of the number of employers for the same industry and year in the other provinces.

$$\text{Instrument}(HHI)_{pst} = \frac{1}{M-1} \sum_{m \neq p} \log\left(\frac{1}{N_{mst}}\right)$$

[19]For example, an IHHI of 10 implies that the market has the same HHI that a market consisting of 10 firms with the same number of employees would have.

[20]The occupation is defined at the 4-digit ISCO level.

where M is the number of provinces, N_{mst} is the number of employers in province m, industry s and year t. Conceptually, this approach provides variations in local concentration that are driven by national-level changes and not by local-specific determinants. A similar strategy was already applied in a similar context by Marinescu et al. (2021), Azar et al. (2020a), and Qiu and Sojourner (2019).

3.6 Results

We restrict the analysis only to those vacancies that report both the province and 2-digit ATECO industry code, this leads to a final sample of 553 132 vacancies, distributed over 4 years, 106 provinces, 380 occupation codes, and 73 industry codes. Tables T.3.2 and T.3.3 show the summary statistics of this final sample.

3.6.1 Effect of labor Market Concentration on Experience and Education

In a well known paper Modestino et al. (2020) show that, in the US, following an increase in the supply of workers, employers requirements in terms of education and experience increase, denoting some form of opportunistic upskilling. This effect should be similar considering firms with stronger monopsony power.

Therefore we start by analyzing the effect of labor market concentration on experience and education. Table T.3.4 reports the estimates of labor market concentration on whether a vacancy requires less than 1 year of experience (*No Exp. required*), the years of experience demanded (*Experience*),[21] whether is required a university degree (*Graduate*), and the total number of skills demanded. Overall labor market concentration is negatively related

[21]Required experience is reported in ranges, therefore we use the midpoint of these ranges to create a variable measuring the years of experience. Some vacancies have missing information on the year of experience, we opted to drop these vacancies; including them does not change the results. For details, see table T.3.2.

with experience and positively with the level of education. Specifically, one standard deviation increase in the labor market concentration increases the probability that the vacancy does not require any experience by 5.6%, i.e. an increase of 1 percentage point.[22] The same change in HHI decreases the amount of experience required by 6 percentage points, or 2.2 percent, which amounts to almost 25 days less of experience required. Furthermore, labor market concentration is positively correlated with the probability that the job ad requires a university degree.

Overall, our results support a different interpretation to Modestino et al. (2020). We observe in fact that an increase in local labor market concentration reduces the experience required, but, at the same time, it increases the demand for graduate workers. These results are in line with the training hypothesis. If employers in a more concentrated labor market are more prone to training new workers, they do not demand that workers already possess job experience; instead, they look for workers who can acquire and learn new competencies fast and efficiently, as signaled by their education level.[23]

Finally, considering the skill variable, we do find evidence of an "upskilling" effect but it is somewhat different from the standard interpretation, in our case an increase in labor market concentration leads to an increase in the number of skills required. However so far we have not analyzed the type and nature of the skills required. The next sections deals with these issues.

[22] Note that for a lin-log model: $\delta = (mean(HHI) + sd(HHI))/mean(HHI)$; $(\hat{\beta} * log(1+\delta)) * 100 = \Delta$. Where Δ is the estimated change in percentage points due to an increase of 1 standard deviation of the independent variable.

[23] It is worth underlining how education does provide not only knowledge and information but also provides a method of study and helps develop problem-solving skills. It teaches how to learn complex and abstract concepts. Considering a signaling model à la Spence (1973), education can also signal the worker's innate abilities to potential recruiters.

3.6.2 Market concentration and skill demand

We start with the broad O*NET classification of the competencies set, Tables T.3.5 and T.3.6 report the results for the ordinary least squares estimations of the binary and tf-idf intensity measure, respectively. Each table includes five different categories of skill/competency as dependent variable: Skill, Knowledge, Ability, (Work) Activity, and (Work) Style.[24] Overall Knowledge is negatively correlated with labor market concentration while work styles activities and skills are positively correlated although the results are sharper when considering the tf-idf measure.

Note that the Knowledge pillar consists in the "organized set of principles and facts", whereas Skills pillar defines "developed capacities to facilitate learning", and Work Activities are "general types of job behaviors occurring on multiple jobs."[25] These results are in line with the training rationale. Employers in more concentrated markets are more willing to provide on-the-job training, so they are more interested in workers that are able to learn faster rather than workers who already possess knowledge. Knowledge pertains competences that are strongly connected with formal training, and can be taught by the firm internally. On the contrary working attitudes such as being a quick learner or being good at interacting with others are less easily trainable and are acquired by the firm on the market through hiring.

To give a clearer sense of these results, Figures F.3.13 and F.3.13 plot the estimated coefficient for all the different competencies and for the two different intensity measures. Regarding the magnitude of the coefficients, a standard deviation rise in the labor market concentration decreases the Knowledge tf-idf score by around 1.5%.The same increase in local labor market concentration, *ceteris paribus*, leads to an increase of Skill tf-idf score by around 1.1%. Therefore, a rise in the HHI decreases the importance of Knowledge

[24]The results are also graphically represented with residualized binscatter plots in figure F.3.13.
[25]In particular, it consists of Mental processes and Interacting with others, see ONET webpage

competencies and increases that of Skill competencies compared to their usual relevance for that occupation.

In order to better explore these issues we regrouped skills and competencies into a classification that allows to shed more light on what type of skills are requested in concentrated markets. Tables T.3.7 and T.3.8 report the results.[26] Social and hard skills are positively related with labor market concentration using both intensity measures. On the other hand cognitive, digital and organisational skills are negatively correlated with labor market concentration using the tf-idf measure while the results are less sharp with the binary intensity measure.

Results presented so far fit with the training rationale. Higher concentration in labor market lead firms to demand less competences that are trainable (e.g. the knowledge pillar) and more that are un-trainable (e.g social skills). However there some results are note completely in line. For example following the training hypothesis we would expect cognitive skills to be positively correlated with market concentration while our results show that the relationship is negative for the tf-idf measure and null for the binary measure.

3.6.3 Skill Demand Heterogeneity across Occupations

In order to shed light into these issues we have analysed separately different classes of occupation. Following the ISCO classification, we divided occupations into high- and medium/low-skill occupations. Specifically, those occupations with the 1-digit ISCO code between 1 and 3 are high skill-occupations, whereas the occupations with codes between 4 and 9 are low/medium-occupations.[27] We therefore estimate separately the effect on high and medium/low occupations. Figures F.3.13 and F.3.13 show the heterogeneous

[26]The results are also graphically represented with residualized binscatter plots in figure F.3.13.
[27]For more details on the classification, see ILO website.

effect of local labor market concentration on the demand for skills. Two results emerge. First the binary measure delivers sharper differences, this is expected as it does not weight skills by their relative importance. Second it emerges a clear difference between high and medium-low skill occupations

Compared with medium-low skill occupations, employers posting vacancies in high-skill occupations in highly concentrated labor markets increase the relative demands for Cognitive skills and reduce the demand for Knowledge. On the contrary, for low-skill occupation Hard and Social skills become relatively more important. Given the different nature of the tasks performed in each occupation class, employees in high-skill occupations are required to perform more complex tasks and duties than employees in low-occupations. Also organizational skills are positively correlated with market concentration for high skills occupations while they are negatively correlated for low skill ones.

As stressed above, results for the binary measure are sharper than those of the tf-idf measure especially for some skills such as cognitive and digital. This can be partly explained by the increased generalized diffusion of these competences. In more concentrated labor market is more common to require such competences: it is in fact more frequent that advertisements contain at least one of these skills (binary measure). At the same time these competences are becoming increasingly required in all vacancies. This reduces their relative weight in the tf-idf measure. We know that labor market concentration is also associated with an increase in the number of skills (table T.3.4). Splitting these estimates by occupation (table T.3.9) shows that this effect is driven by high skill occupations. Thus labor market concentration is associated with an increase in the number of competences in high-skill occupations. In addition cognitive and digital skills are increasing but also becoming more general. This explains why the effect on the tf-idf measure becomes zero or even negative.

3.6.4 Alternative measure of skill intensity: Effective use

The previous paragraph shows that there is not an ideal approach to measure skill intensity as there is always a tension between skills that are in high demand in general and skills that are in high demand because are occupation specific. A possible way to reconcile the different approaches is to rely on the *effective-use* measure described in Alabdulkareem et al. (2018). The intuition is simple starting from the tf-idf measure, or more precisely a variant of it, it is possible to identify a threshold that define the average demand for skill within an occupation. The *effective use* is a dichotomous measure that takes the value of 1 if that particular skill is demanded more than the average and 0 otherwise.

Figure F.3.13 displays the estimates following the same methodology described in Section 3.5. The *effective-use* measure shows clearer differences between high and low skill occupations which reinforce the interpretation provided so far. Compared with low-skill occupations, employers posting vacancies in high-skill occupations in highly concentrated labor markets increase the relative demands for Cognitive skills and reduce the demand for Knowledge. Moreover digital skills are positively correlated with labor market concentration for high skill occupations while they are negatively correlated for medium-low skill occupations.

Overall these results support the training rationale as they can be explained in terms of different training requirements of high and low-skill occupations. Presumably new hires in high-skill occupations need to learn in-depth and complex competencies, which are difficult to be taught through mentoring or assistance from senior colleagues, instead these competences require formal teaching as in-class courses. For example the type of organizational skills that are needed for high skill occupations are generally managerial skills which can be acquired in graduate studies. Hence firms in more concentrated markets tend to demand more of these skills alongside with a higher level of education. Table T.3.9

shows that labor market concentration increases the level of education and the share of graduates and this effect is higher for high skill occupations. On the other hand new hires in low-skill occupations, performing simpler duties and tasks, can learn by being assisted and guided from an experienced colleague. Thus, having good social and hard skill can particularly help recruits in low-skill occupations to learn the required competencies. While in high-skill occupations, where workers are more likely to be trained through more formal training activities, cognitive abilities become particularly important to enable the workers to learn and acquire new knowledge. Finally, it is important to stress that several cognitive skills, being often general, are less likely to be explicitly mentioned for high skill occupations as they are subsumed by the higher level of education. This can explain the low significance of the coefficient for high skill occupations.

3.7 Additional Robustness Checks

Although, as explained in section 3.5, results are robust to different specifications and definitions, we present some additional robustness checks. First, we present the results of an instrumental variable approach. Second, we introduce additional controls to account for local labor market conditions.

3.7.1 Instrumental variable approach

As explained in section 3.5 the IV approach consists in instrumenting the changes in the potential endogenous variable for a specific location with the changes of a determinant of this endogenous variable in other locations. In our framework, we instrument the HHI of a market (combination of province, industry, and year) with the average of the logarithm of the inverse of the number of employers across the other markets of the same industry and in the same year. We acknowledge that our IV strategy is far from perfect as it relies on the time variation of the skill intensity measure neglecting the variability cross province. These results should therefore be taken with caution.

Figure F.3.13 plots the estimated coefficients for all the different competencies for the tf-idf intensity measure. With IV estimates, the magnitude of the impact of labor market concentration on competencies demand appears to be greater. The TSLS results are also in line with the results obtained with the OLS specifications. Specifically, the negative impact of labor market concentration on Knowledge persists, as well as the positive effect on Social skills.

3.7.2 Controlling for unemployment level

A possible bias might emerge if firms behave differently in their hiring decisions according to the level of unemployment, which in turn could change the number of competencies demanded by the employers. Thus, if the unemployment rate correlates with the concentration level, this can bias the estimates obtained in section 3.6. For example, Bilal (2021) observes that employers can have different time opportunity costs to find a new worker depending on their productivity, and thus behave differently according to the level of unemployment. Productive firms are less willing to spend much time for searching potential candidates, while low productive firms have less incentive to accelerate the hiring procedure. To account for the possible effect of the unemployment rate, tables T.3.12 and T.3.13 include a control for the level of unemployment in the local labor market, confirming the main findings.

3.8 Discussion and Conclusion

What are the effects of local labor market concentration on the skills and competencies demanded by employers? By exploiting Italian Online Job Advertisements, we showed that labor market concentration increases the overall amount of competencies requested, in line with the upskilling phenomenon observed in the literature. However, more interestingly, we observed that not only the number of competencies demanded changes, but also its composition. We show that employers in a highly concentrated labor market demand competencies associated with the ability of workers to learn faster (e.g., Social competencies) rather than actual knowledge. They also require less experience but higher education. These results align with the training rationale: employers in highly concentrated labor markets are more likely to provide training to their employees. Thus, they are relatively less interested in job-specific knowledge and competencies but more in attitudes and skills that allow them to learn faster. We also observe heterogeneity in skill demand across high and low-skill occupations. Specifically, the negative effect of concentration on knowledge competencies is driven by high skill occupation, while the positive impact on Social competencies is driven by low and medium skill ones. Also this is in line with the training hypothesis. In high skill occupation due to the level of complexity of the knowledge required, training is more likely to be provided in a more formal way, e.g. through in-class courses. In contrast, for low-occupation jobs training can be provided through on-the-job cross-training with other employees. Unfortunately, we do not have data on how the training is carried out; therefore, this question is left for future research.

Our paper has relevant policy implications. In addition to cross countries differences in labor market regulations (Filippetti and Guy, 2020) our findings suggest that policy authorities should consider the local labor market structure when studying workforce development programs aimed at bridging the skill gap of displaced workers. Analogously market concentration is a crucial element to be considered when designing practical solutions to tackle rapid technological change (Vona and Consoli, 2014; Ciarli et al., 2021).

3.9 List of Tables and Figures

3.9.1 List of Tables

Table T.3.1: Description of the competencies groups

Group	Description
GROUP I	*(based on first level O*NET classification)*
Knowledge	Organized sets of principles and facts applying in general domains.
Skills	Developed capacities that facilitate learning or the more rapid acquisition of knowledge.
Abilities	Enduring attributes of the individual that influence performance
Work Activities	General types of job behaviors occurring on multiple jobs.
Work Styles	Personal characteristics that can affect how well someone performs a job.
GROUP II	*(Own classification based on finest skill categorization)*
Cognitive	Cognitive Abilities, Complex Problem Solving Skills, Mental Processes
Social	Interacting with others
Digital	Software and Technology
Hard Skills	Technical skills, Tools, Work output
Organizational	System skills, Resource Management Skills

Note: The classification of the first group is based on the O*NET pillars classification, for more detail see O*NET webpage. The categories of the second group follows our own classification based on detailed level skills.

Table T.3.2: Summary statistics

	N	mean	sd	p25	median	p75
HHI	553,132	0.132	0.201	0.0219	0.0538	0.136
HHI*10k	553,132	1319.215	2011.002	219	538	1,364
log(HHI*10k)	553,132	6.355	1.293	5.39	6.29	7.22
No. skills per ad	553,132	6.557	7.266	2	4	9
Education index [1,8]	553,132	4.461	1.164	4	4	5
Primary	553,132	0.021	0.145	0	0	0
Lower secondary	553,132	0.000	0.014	0	0	0
Post-secondary	553,132	0.037	0.189	0	0	0
Short-cycle tertiary	553,132	0.691	0.462	0	1	1
Upper secondary	553,132	0.005	0.068	0	0	0
Bachelor or equivalent	553,132	0.188	0.391	0	0	0
Master or equivalent	553,132	0.050	0.217	0	0	0
Doctoral or equivalent	553,132	0.008	0.091	0	0	0
Experience index [1,8]	375,182	3.662	1.769	3	4	4
No experience	375,182	0.153	0.360	0	0	0
<= 1 year	375,182	0.043	0.204	0	0	0
(1-2] years	375,182	0.246	0.431	0	0	0
(2-4] years	375,182	0.371	0.483	0	0	1
(4-6] years	375,182	0.078	0.267	0	0	0
(6-8] years	375,182	0.013	0.115	0	0	0
(8-10] years	375,182	0.029	0.167	0	0	0
> 10 years	375,182	0.066	0.248	0	0	0

Table T.3.3: Summary statistics, skill/competency classification

GROUP I	N	mean	sd	p25	median	p75
Skills						
Binary	553,132	0.332	0.471	0	0	1
TF-IDF	553,132	0.099	0.191	0	0.0358	0.119
Knowledge						
Binary	553,132	0.705	0.456	0	1	1
TF-IDF	553,132	0.082	0.180	0	0.0215	0.0868
Ability						
Binary	553,132	0.070	0.256	0	0	0
TF-IDF	553,132	0.017	0.108	0	0	0
Activities						
Binary	553,132	0.676	0.468	0	1	1
TF-IDF	553,132	0.094	0.190	0	0.0303	0.104
Work Style						
Binary	553,132	0.515	0.500	0	1	1
TF-IDF	553,132	0.103	0.219	0	0.0151	0.111
GROUP II	N	mean	sd	p25	median	p75
Cognitive						
Binary	553,132	0.353	0.478	0	0	1
TF-IDF	553,132	0.076	0.213	0	0	0.0625
Hard-Skills						
Binary	553,132	0.414	0.493	0	0	1
TF-IDF	553,132	0.089	0.205	0	0	0.0862
Organizational						
Binary	553,132	0.122	0.327	0	0	0
TF-IDF	553,132	0.022	0.090	0	0	0
Digital						
Binary	553,132	0.173	0.378	0	0	0
TF-IDF	553,132	0.024	0.095	0	0	0

Table T.3.4: OLS estimates of labor market concentration on No. skills, experience, and education

	No competencies per ad	No Exp. required	Experience	Graduate
log(HHI)	0.0503***	0.0085***	-0.0507***	0.0062***
	(0.0102)	(0.0010)	(0.0073)	(0.0007)
Year FE	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓
MDV	6.557	0.197	2.971	0.246
mean(HHI*10k)	1,319	1,213	1,213	1,319
R^2	0.500	0.078	0.092	0.238
N	553,030	375,122	375,122	553,030

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables (1) *No. competencies per ad*, (2) *No Exp. required*, (3) *Experience*, and (4) *Graduate* which define (1) the number of competencies demanded in the vacancy, if the vacancy demands (2) less than 1 year of experience, (3) the midpoint-approximation years of experience demanded, and (4) a bachelor's degree. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table T.3.5: OLS estimates of labor market concentration on skill/competency demand (group 1), binary measure.

	Skill	Knowledge	Ability	Activities	Styles
log(HHI)	0.0005	-0.0036***	0.0019***	0.0020*	0.0003
	(0.0008)	(0.0007)	(0.0005)	(0.0008)	(0.0009)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.332	0.705	0.070	0.676	0.515
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.312	0.371	0.145	0.344	0.199
N	553,030	553,030	553,030	553,030	553,030

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the binary intensity measure of the broader skill classification (group 1) described in section 3.4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table T.3.6: OLS estimates of labor market concentration on skill/competency demand (group 1), tf-idf measure.

	Skills	Knowledge	Ability	Activities	Styles
log(HHI)	0.0009*	-0.0009*	-0.0003	0.0008*	0.0008
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0004)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.099	0.082	0.017	0.094	0.103
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.133	0.140	0.017	0.124	0.112
N	553,030	553,030	553,030	553,030	553,030

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the tf-idf intensity measure of the broader skill classification (group 1) described in section 3.4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table T.3.7: OLS estimates of labor market concentration on skill/competency demand (group 2), binary measure.

	Cognitive	Hard Skills	Organizational	Social	Digital
log(HHI)	0.0001	0.0037***	-0.0006	0.0029***	0.0007
	(0.0008)	(0.0008)	(0.0006)	(0.0008)	(0.0006)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.353	0.414	0.122	0.457	0.173
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.323	0.279	0.215	0.387	0.361
N	553,030	553,030	553,030	553,030	553,030

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the binary intensity measure of the finer skill classification (group 2) described in section 3.4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

Table T.3.8: OLS estimates of labor market concentration on skill/competency demand (group 2), tf-idf measure.

	Cognitive	HardSkills	Organizat	Social	Digital
log(HHI)	-0.0008*	0.0014***	-0.0006***	0.0010**	-0.0004*
	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0002)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.076	0.089	0.022	0.060	0.024
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.035	0.078	0.061	0.090	0.054
N	553,030	553,030	553,030	553,030	553,030

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the tf-idf intensity measure of the finer skill classification (group 2) described in section 3.4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table T.3.9: OLS estimates of labor market concentration on No. skills, experience, and education, separated by occupation-skill level.

	No competencies per ad		Experience		Graduate	
	Low	High	Low	High	Low	High
log(HHI)	-0.0118	0.1214***	-0.0414***	-0.0601***	0.0047***	0.0076***
	(0.0078)	(0.0193)	(0.0093)	(0.0114)	(0.0008)	(0.0013)
Year FE	✓	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓	✓
MDV	3.409	9.643	2.655	3.287	0.111	0.378
mean(HHI*10k)	1,298	1,340	1,177	1,249	1,298	1,340
R^2	0.311	0.409	0.114	0.064	0.115	0.183
N	273,788	279,239	187,282	187,839	273,788	279,239

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the OLS regression outputs separated fr high and low skill occupations using as dependent variables (1) *No. competencies per ad*, (2) *Experience*, and (3) *Graduate* which define (1) the number of competencies demanded in the vacancy, (2) the midpoint-approximation years of experience demanded, and if the vacancy demands (3) at least a bachelor's degree. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table T.3.10: TSLS estimates of labor market concentration on vacancy competencies demand (tf-idf measure)

	Skills	Knowledge	Ability	Activities	Styles
log(HHI)	0.0009	-0.0025**	-0.0006	0.0009	0.0030**
	(0.0009)	(0.0008)	(0.0005)	(0.0009)	(0.0010)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.078	0.306	0.008	0.302	0.154
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
F	111,822	111,822	111,822	111,822	111,822
N	553,030	553,030	553,030	553,030	553,030

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the TSLS regression outputs using as dependent variables the tf-idf intensity measure of the broader skill classification (group 1) described in section 3.4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table T.3.11: TSLS estimates of labor market concentration on vacancy competencies demand (tf-idf measure)

	Cognitive	HardSkills	Organizat	Social	Digital
log(HHI)	-0.0050***	0.0016	-0.0029***	0.0028***	0.0000
	(0.0010)	(0.0010)	(0.0004)	(0.0008)	(0.0005)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.097	0.121	0.015	0.122	0.023
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
F	111,822	111,822	111,822	111,822	111,822
N	553,030	553,030	553,030	553,030	553,030

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the TSLS regression outputs using as dependent variables the tf-idf intensity measure of the finer skill classification (group 2) described in section 3.4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table T.3.12: OLS estimates of labor market concentration on skill/competency demand (group 1), tf-idf measure; controlling for unemployment rate.

	Skills	Knowledge	Ability	Activities	Styles
log(HHI)	0.0009*	-0.0009*	-0.0003	0.0008*	0.0008
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0004)
unemploym.	0.0006	0.0003	0.0004*	0.0008*	0.0008*
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0004)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.099	0.082	0.017	0.094	0.103
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.133	0.140	0.017	0.124	0.112
N	553,030	553,030	553,030	553,030	553,030

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.
Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the tf-idf intensity measure of the broader skill classification (group 1) described in section 3.4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table T.3.13: OLS estimates of labor market concentration on skill/competency demand (group 2), tf-idf measure; controlling for unemployment rate.

	Cognitive	HardSkills	Organizat	Social	Digital
log(HHI)	-0.0008*	0.0014***	-0.0006***	0.0010**	-0.0004*
	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0002)
unemploym.	0.0002	0.0004	-0.0001	0.0002	0.0003*
	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0002)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.076	0.089	0.022	0.060	0.024
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.035	0.078	0.061	0.090	0.054
N	553,030	553,030	553,030	553,030	553,030

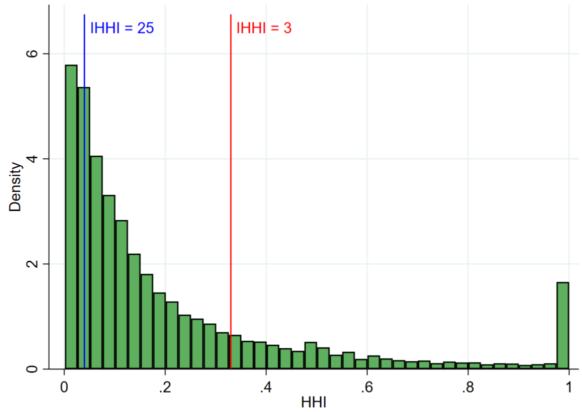
Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the tf-idf intensity measure of the finer skill classification (group 2) described in section 3.4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

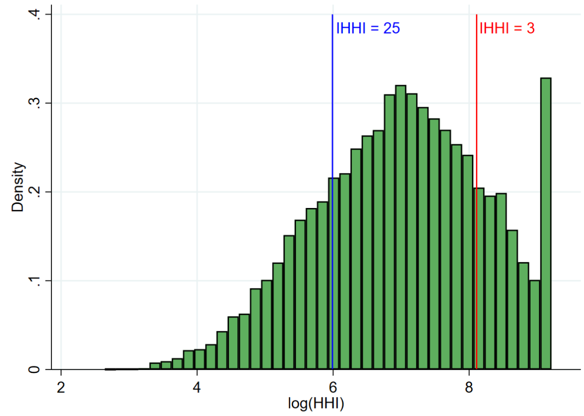
3.9.2 List of Figures

Figure F.3.13: Employment concentration in the Italian local labor markets (2015-2018)

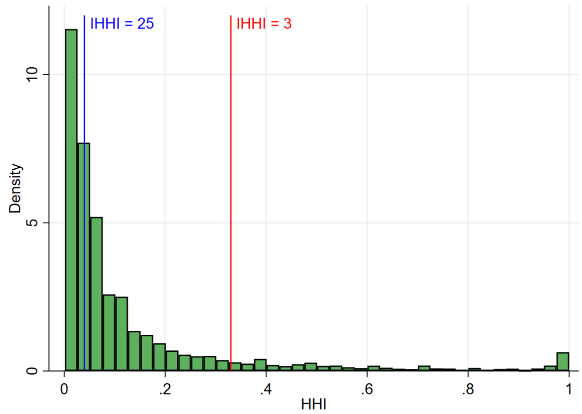
(a) Average across Markets, level



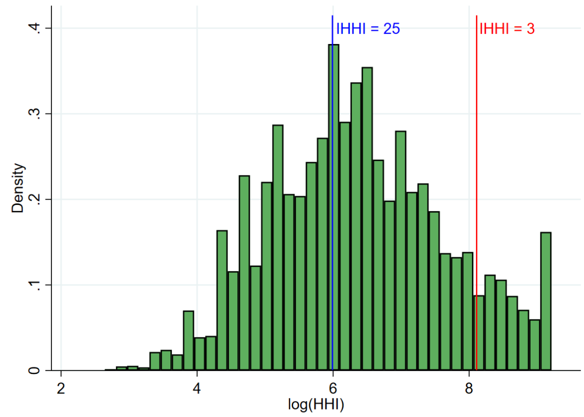
(b) Average across Markets, logarithm



(c) Average across Job Ads, level



(d) Average across Job Ads, logarithm

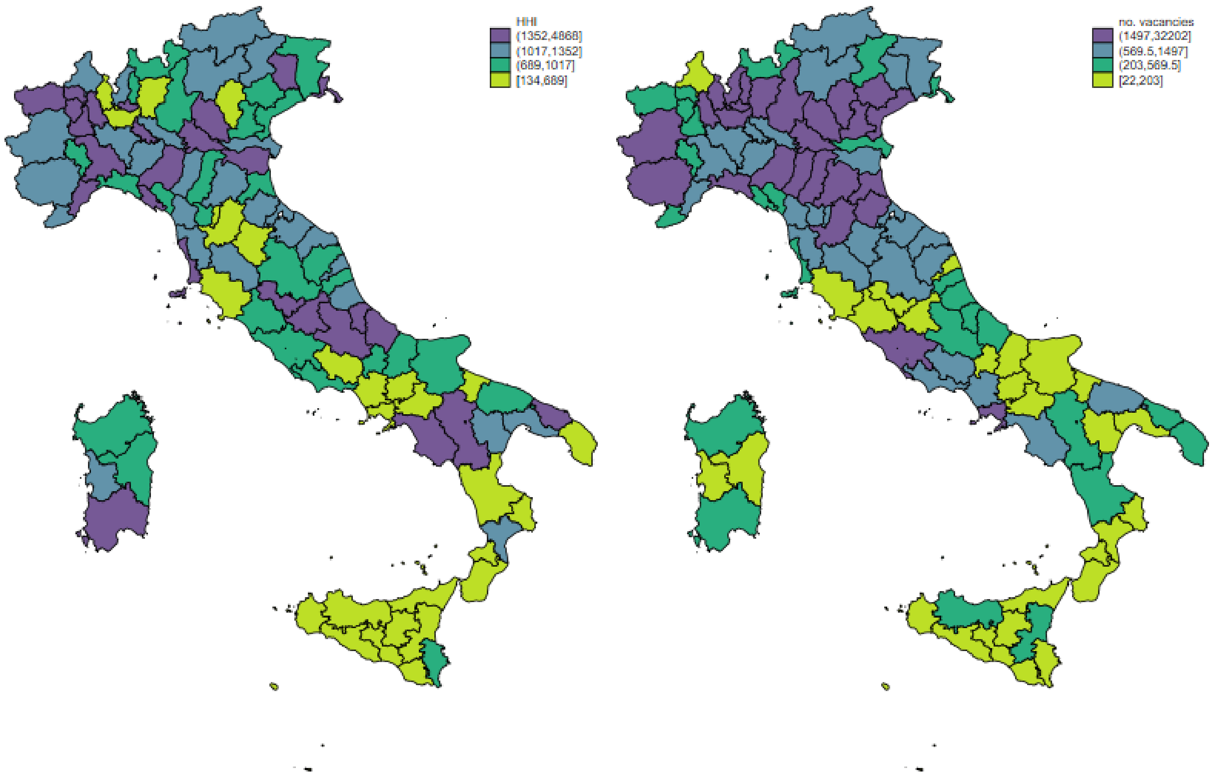


Authors' calculations on AIDA data 2015-2018. The HHI is computed at the local labor market level, which is define as a combination of Province, Ateco 2-digit, and year. The two graphs in the top of the figure are calculated taking the average across local labor market. The two graphs in the bottom of the figure are calculated taking the average across job ads. The logarithm are taken on the HHI multiplied by 10'000. The IHHI defines the Inverse Herfindahl-Hirschman Index, which can be interpreted as the number of equally sized firms that will obtain the same HHI.

Figure F.3.13: Employment concentration and number of vacancies across Italian provinces (2018)

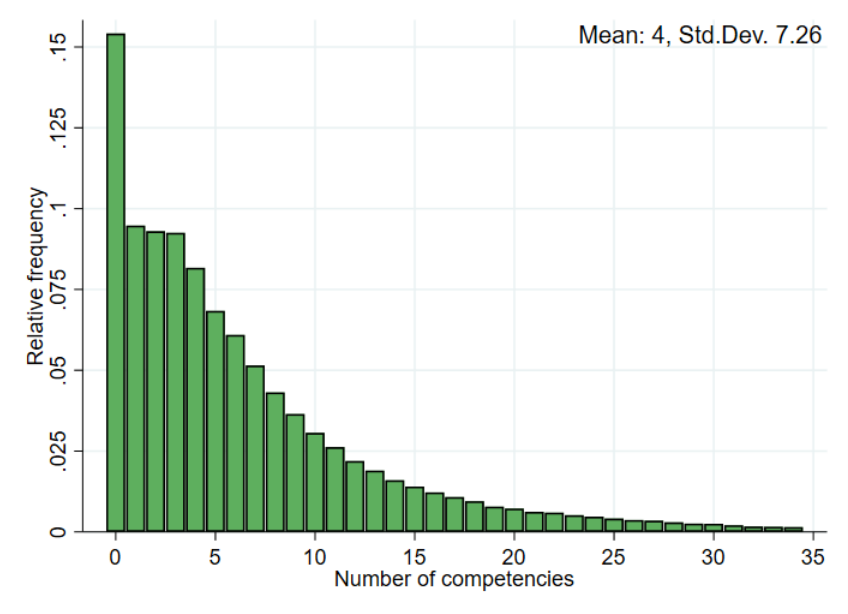
(a) Average local-HHI, weighted by industry employment level

(b) Total number of vacancies posted across provinces



Authors' calculations on AIDA and WollyBi data of 2018. Figure (a) shows the average HHI computed at the local labor market level, which is define as a combination of Province, Ateco 2-digit, and year. These measures are aggregated at the provincial level, weighted by the number of employees in each industry (2digit Ateco). Figure (b) shows the total number of vacancies posted for each province across 2018.

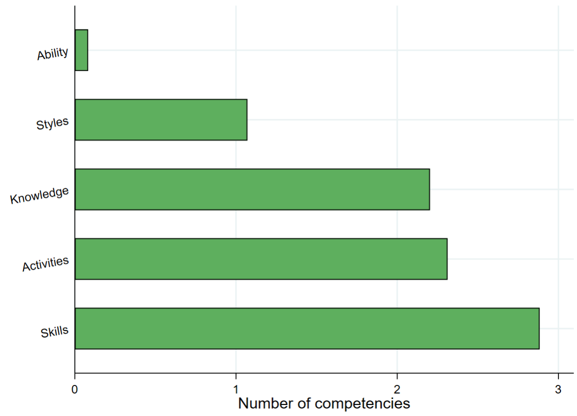
Figure F.3.13: Distribution of number of competencies per job ad



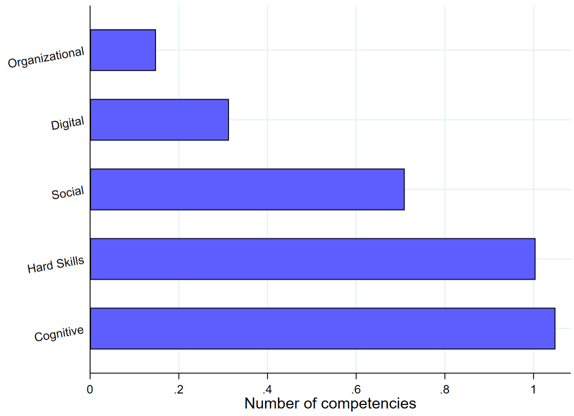
Authors' calculations on AIDA and WollyBi data of 2015-2018. Distribution of the competencies demanded, where the competencies are defined as the finest level of the O*NET taxonomy.

Figure F.3.13: Average number of competencies by type per job ad

(a) Group 1 competencies

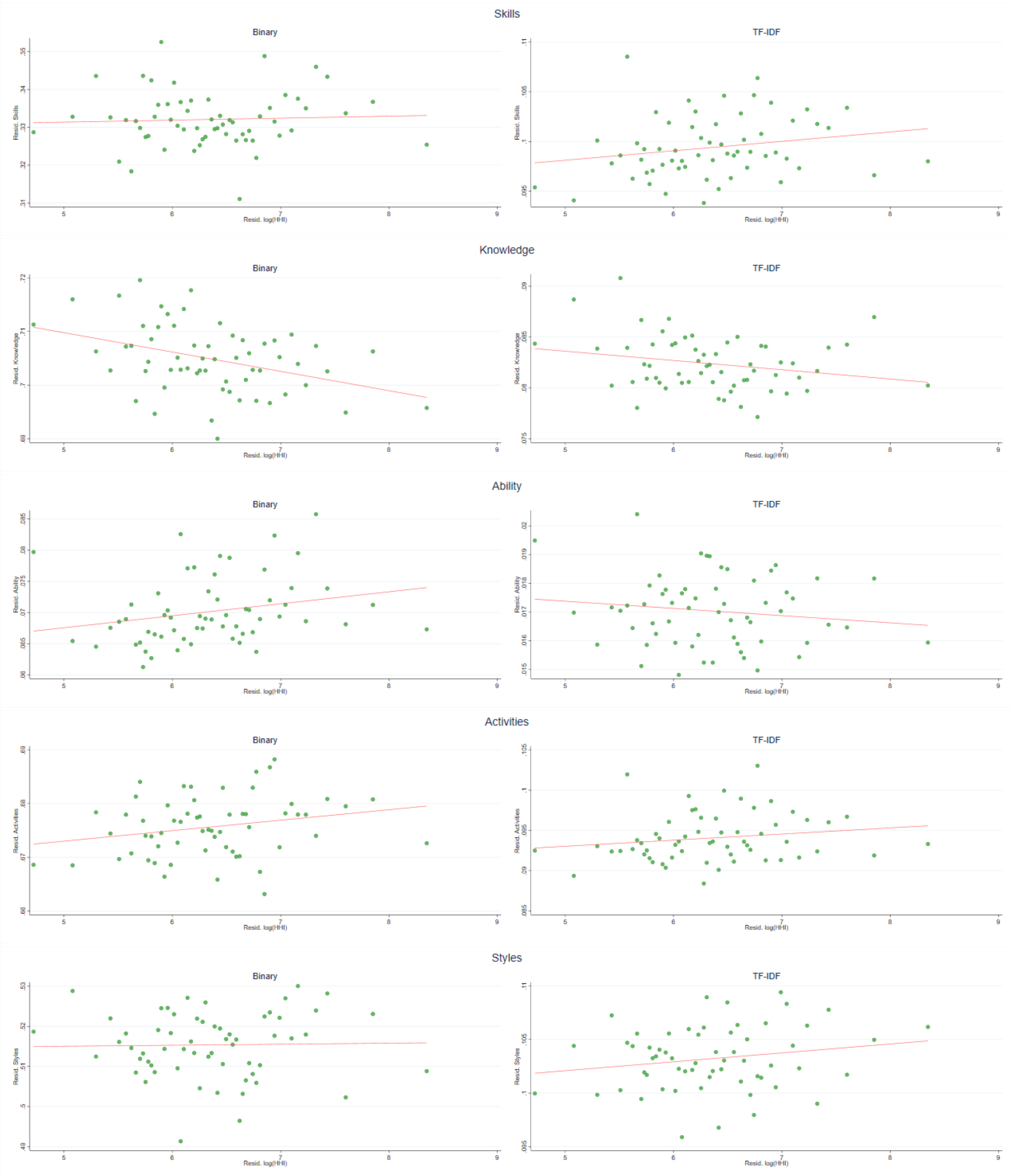


(b) Group 2 competencies



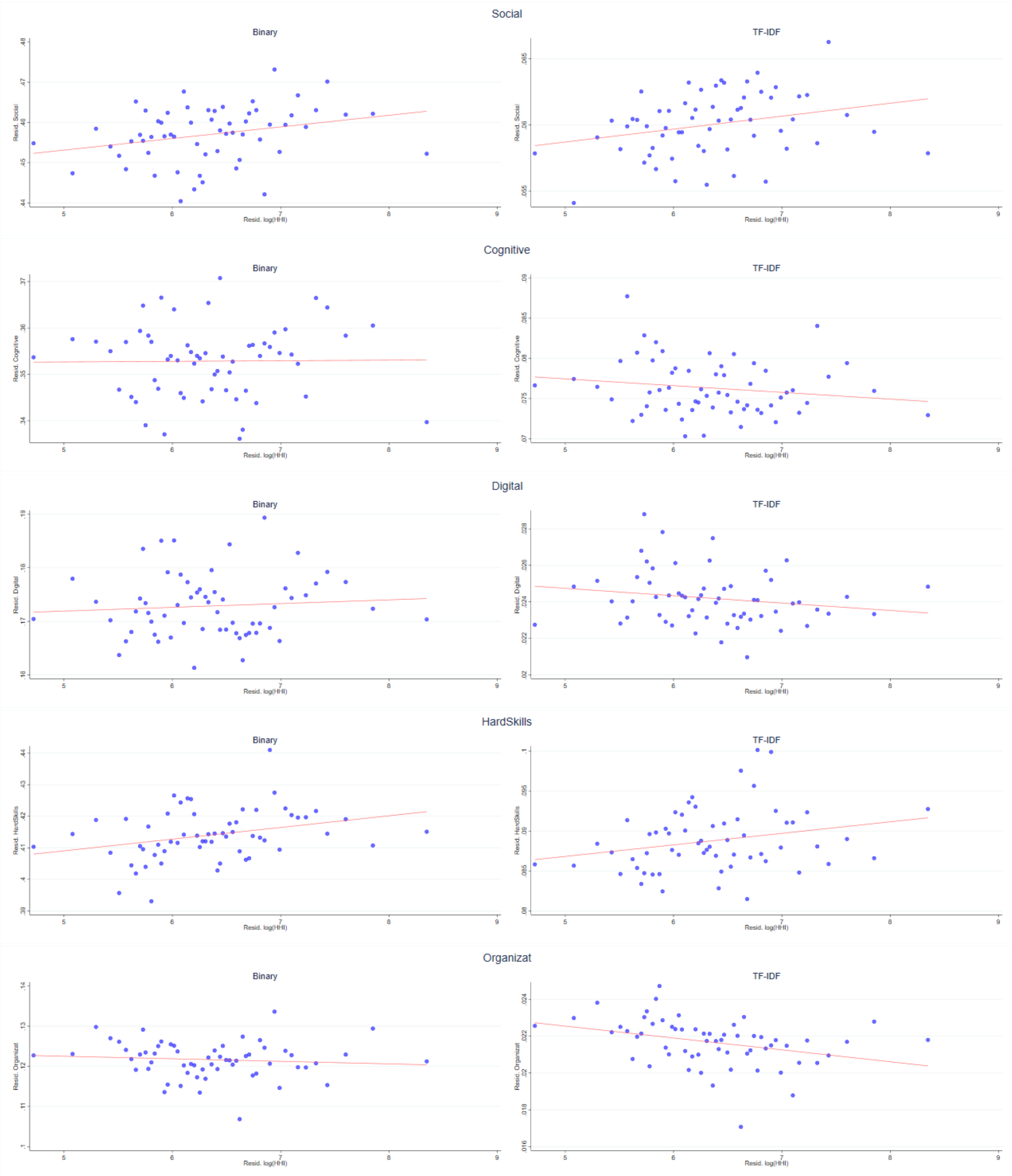
Authors' calculations on AIDA and WollyBi data of 2015-2018. Average number of distinct competencies demanded per skill category, where the competencies are defined as the finest level of the O*NET taxonomy.

Figure F.3.13: Binned scatter plot of labor concentration on demand for the competencies in group 1



Authors' calculations on AIDA and WollyBi data of 2015-2018. Note: The residuals are computed using as regressors occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects.

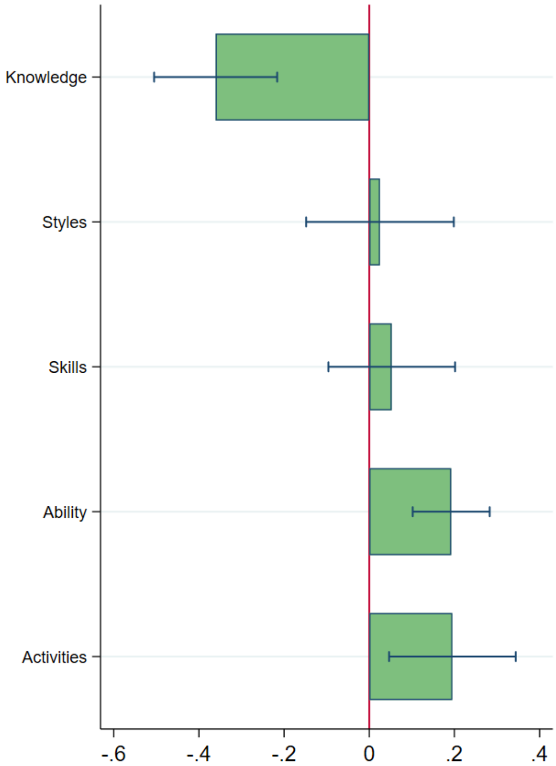
Figure F.3.13: Binned scatter plot of labor concentration on demand for the competencies in group 2



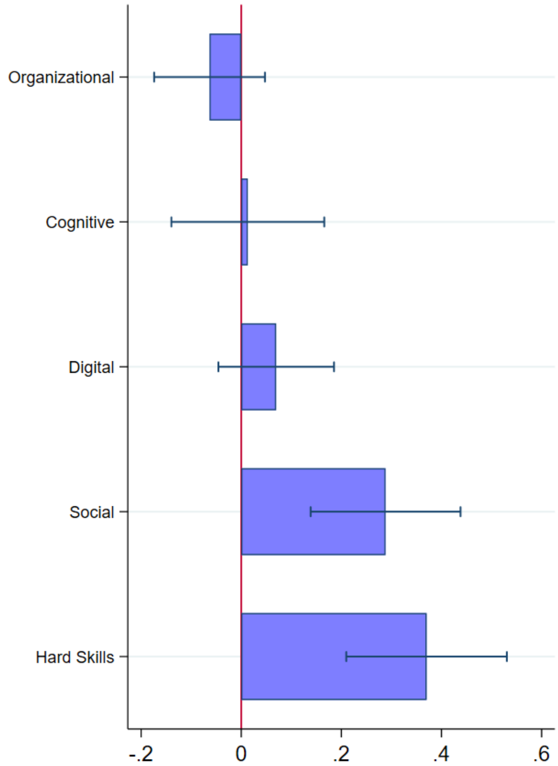
Authors' calculations on AIDA and WollyBi data of 2015-2018. Note: The residuals are computed using as regressors occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects.

Figure F.3.13: Coefficients plots of labor concentration on competencies demand (binary measure)

(a) Group 1 competencies

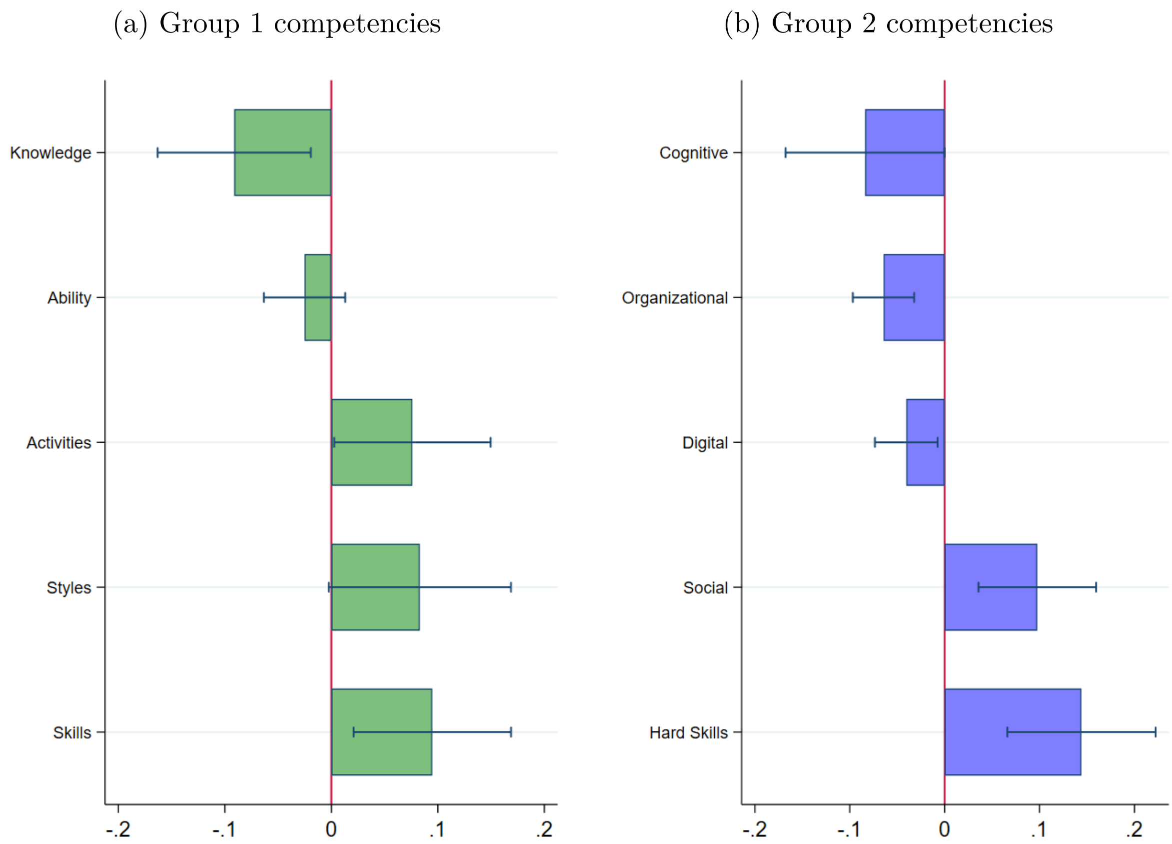


(b) Group 2 competencies



Authors' calculations on AIDA and WollyBi data of 2015-2018. Note: The Figure plots the OLS coefficient and 95% confidence interval of log. HHI on the probability that a vacancy is demanding that particular skill category. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects.

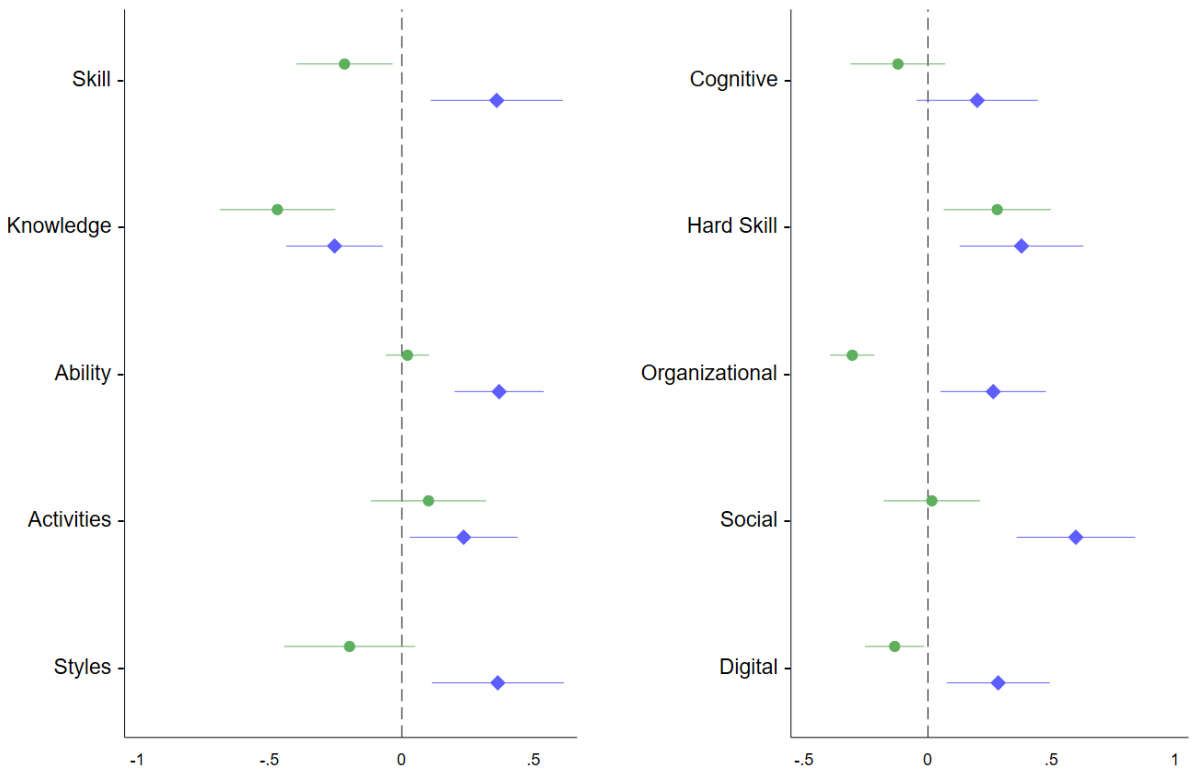
Figure F.3.13: OLS coefficients plots of labor concentration on competencies demand (TF-IDF measure)



Authors' calculations on AIDA and WollyBi data of 2015-2018. Note: The Figure plots the OLS coefficient and 95% confidence interval of log. HHI on the tf-idf score of that particular skill category. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects.

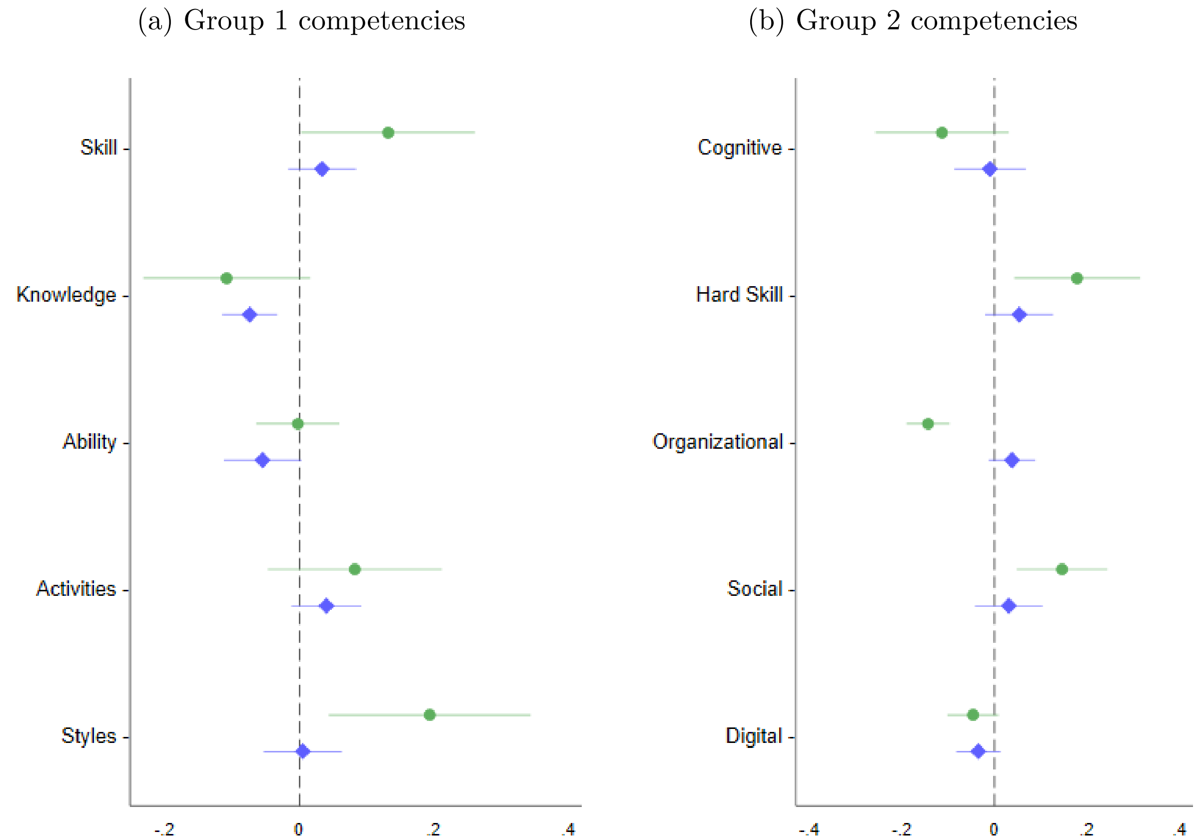
Figure F.3.13: Coefficients plots of labor concentration on competencies demand by high- or low-occupation skill (binary measure)

(a) Group 1 competencies (b) Group 2 competencies



Authors' calculations on AIDA and WollyBi data of 2015-2018. The Figure plots the OLS coefficient and 95% confidence interval of log. HHI on the probability that a vacancy is demanding that particular skill category, separated for high and low skill occupations. The green circles shows the estimates for low-skill occupations, while the blue diamonds the estimates for high-skill occupations. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects.

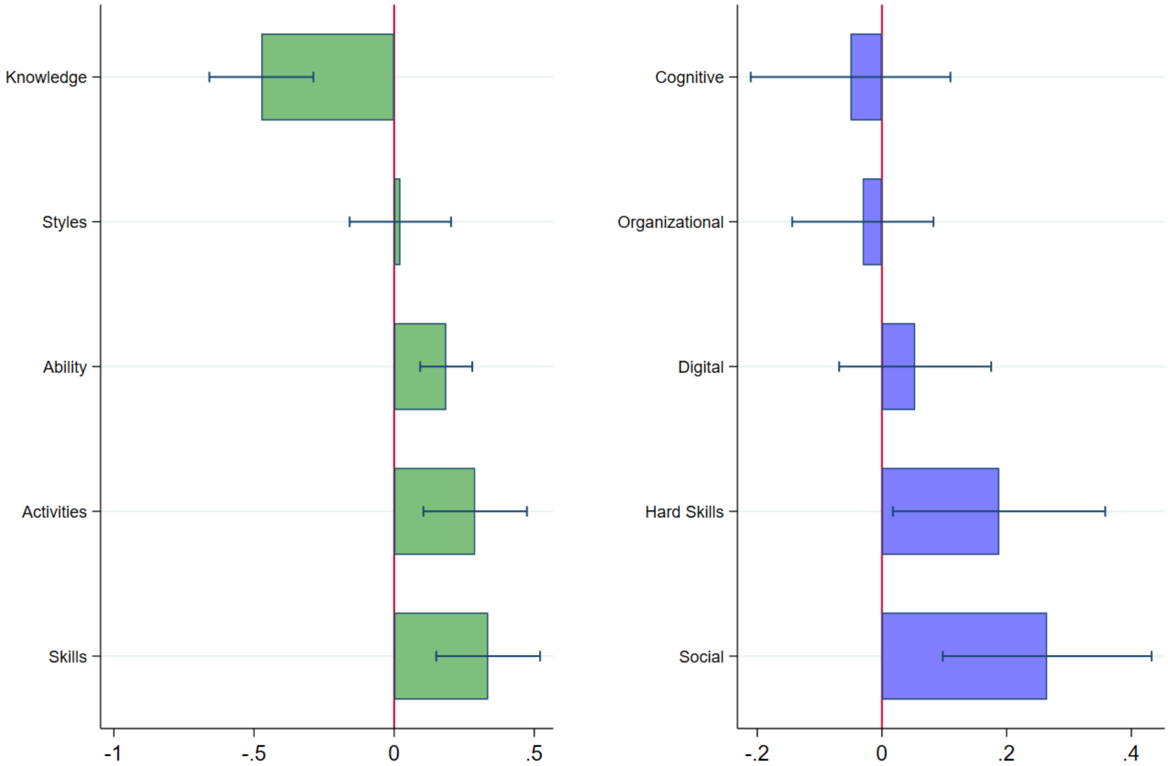
Figure F.3.13: Coefficients plots of labor concentration on competencies demand by high- or low-occupation skill (tf-idf measure)



Authors' calculations on AIDA and WollyBi data of 2015-2018. The Figure plots the OLS coefficient and 95% confidence interval of log. HHI on the tf-idf score of that particular skill category, separated for high and low skill occupations. The green circles shows the estimates for low-skill occupations, while the blue diamonds the estimates for high-skill occupations. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects.

Figure F.3.13: OLS coefficients plots of labor concentration on competencies demand (effective-use measure)

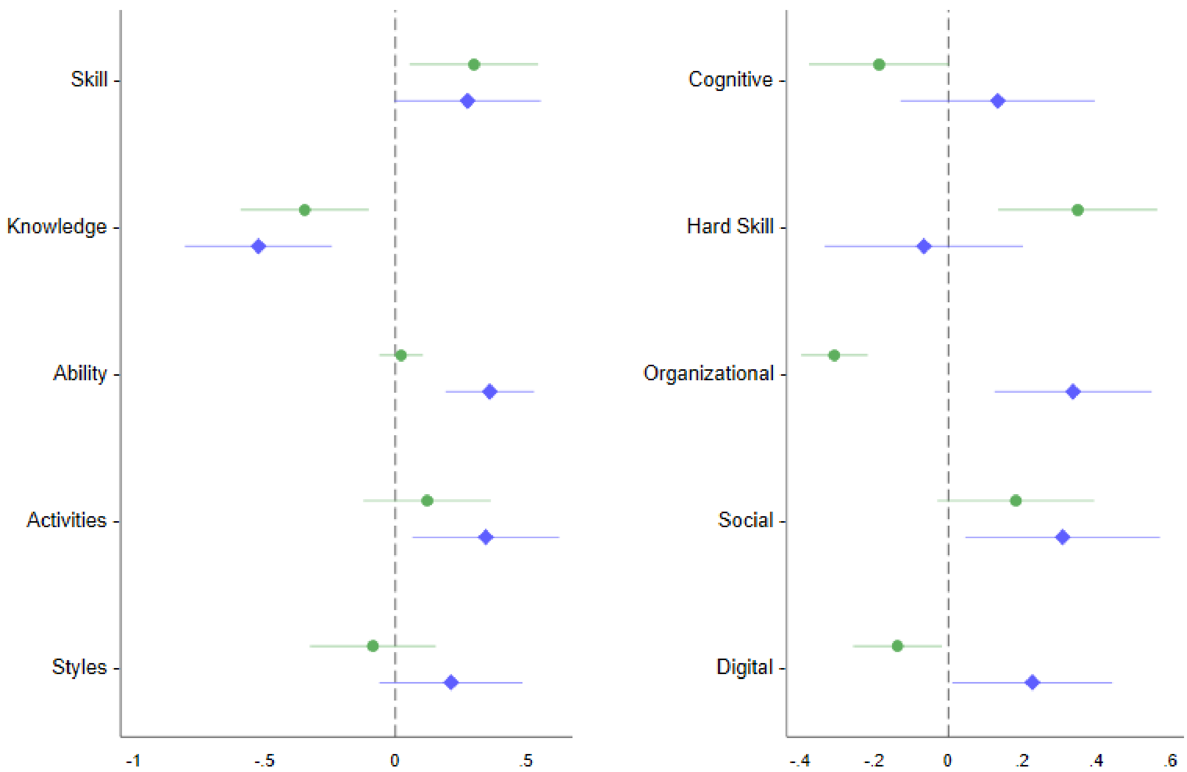
(a) Group 1 competencies (b) Group 2 competencies



Authors' calculations on AIDA and WollyBi data of2015-2018. The Figure plots the OLS coefficient and 95% confidence interval of log. HHI on the effective-use score for that particular skill category, variable described in Section 3.6.4. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects.

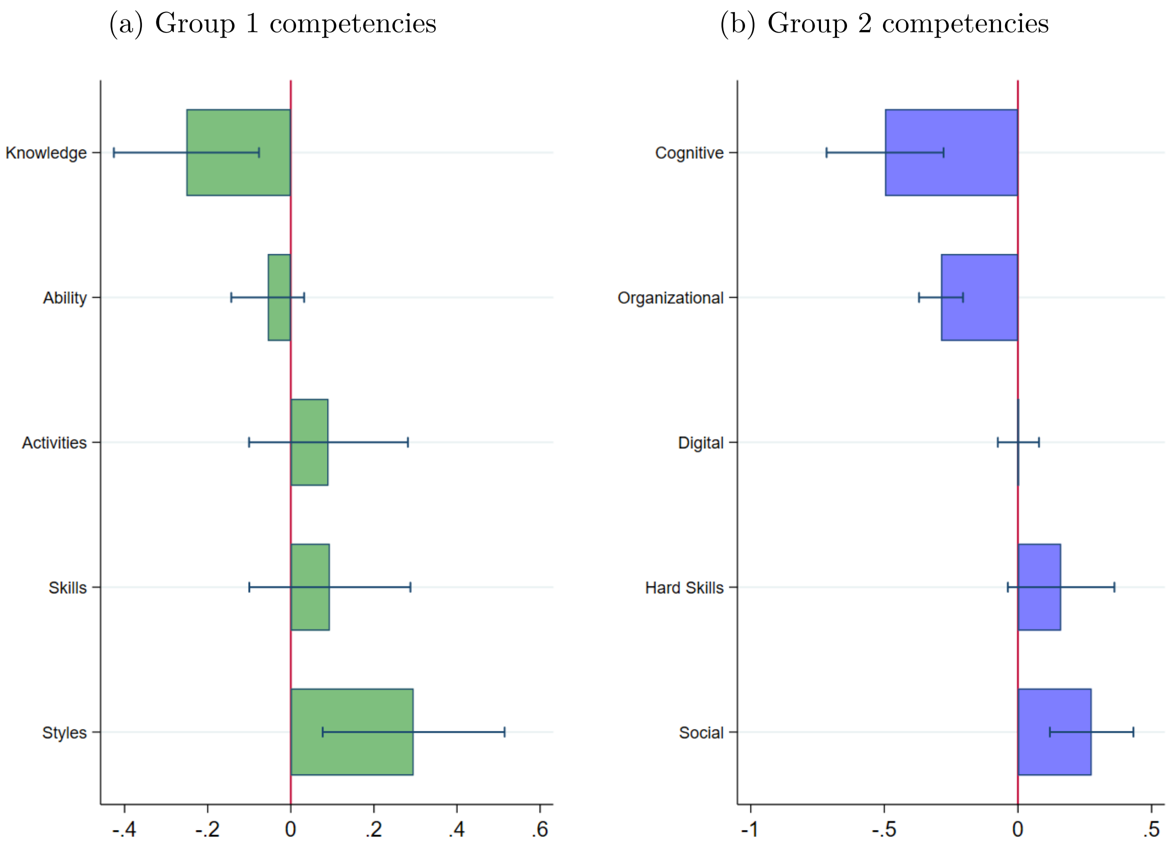
Figure F.3.13: OLS Coefficients plots of labor concentration on competencies demand by high- or low-occupation skill (effective-use measure)

(a) Group 1 competencies (b) Group 2 competencies



Authors' calculations on AIDA and WollyBi data of 2015-2018. The Figure plots the OLS coefficient and 95% confidence interval of log. HHI on the effective-use score of that particular skill category, separated for high and low skill occupations. The green circles shows the estimates for low-skill occupations, while the blue diamonds the estimates for high-skill occupations. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects.

Figure F.3.13: TSLS coefficients plots of labor concentration on competencies demand (TF-IDF measure)



Authors' calculations on AIDA and WollyBi data of2015-2018. The Figure plots the TSLS coefficient and 95% confidence interval of log. HHI on the tf-idf score of that particular skill category. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects.

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F Online Appendix

Model solution

This section provides detailed derivations of mathematical formulae that appear in the main text, section 3.3.

Firm's problem

In addition to the level of trainable (T) and untrainable (U) competence the workforce should have, the firm choose also the amount of training (A) to provide to her workforce. This leads to the following maximization problem,

$$Y = \max_{A,T,U} \left[\left(A^{\alpha} T^{1-\alpha} \right)^{\frac{\theta-1}{\theta}} + U^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} - \tau A - C(W,N)N$$

$$\text{s.t.} \quad N = T + U$$

The first order conditions lead to

$$Y^{-1} \left(A^{\alpha} T^{1-\alpha} \right)^{\frac{-1}{\theta}} A^{\alpha} A^{-1} T^{1-\alpha} (\alpha) = \tau \tag{3.5}$$

$$Y^{-1} \left(A^{\alpha} T^{1-\alpha} \right)^{\frac{\theta-1}{\theta}} T^{-1} (1-\alpha) = (1+e(N))C(W,N) \tag{3.6}$$

$$Y^{-1} U^{-\frac{1}{\theta}} = (1+e(N))C(W,N) \tag{3.7}$$

Dividing 3.5 over 3.6,

$$A = \frac{\alpha}{1-\alpha} \frac{(1+e(N))C(W,N)}{\tau} T$$

Then substituting it into 3.6

$$Y^{-1}\left[\left(\frac{\alpha}{1-\alpha}\right)^{\alpha}\left(\frac{(1+e(N))C(W,N)}{\tau}\right)^{\alpha}T^{\alpha}T^{1-\alpha}\right]^{\frac{\theta-1}{\theta}}T^{-1}(1-\alpha)=(1+e(N))C(W,N)$$

Divide this on 3.7

$$\frac{T}{U}=\left[\frac{\alpha}{1-\alpha}\right]^{\alpha(\theta-1)}\left[\frac{(1+e(N))C(W,N)}{\tau}\right]^{\alpha(\theta-1)}(1-\alpha)^{\theta}$$

Considering a rise of the HHI that increases the average employment share for each labour input keeping the level of input unchanged. One can think of the closure of some of the competing firms reducing the number of the competitors in a local labour market. Assume this HHI rise affects the two inputs market at the same way, i.e. it increases the inverse labour supply elasticity for both the trainable and untrainable inputs of the same amount.[28]

$$\frac{\partial T/U}{\partial HHI}\propto\frac{\alpha(\theta-1)}{\tau}\left[\frac{(1+e(N))C(W,N)}{\tau}\right]^{\alpha(\theta-1)-1}\frac{\partial}{\partial N}(1+e(N)C(W,N))$$

Since

$$e(N)=\frac{\partial C}{\partial N}\frac{N}{C}\quad\Rightarrow(1+e(N))C=C'_{N}N+C>0$$
$$\frac{\partial}{\partial N}(1+e(N)C(W,N))=(C''_{NN}N+2C'_{N})>0$$

Because $C'_N>0$, $C''_{NN}\geq 0$, and $\theta<1$

$$\frac{\partial T/U}{\partial HHI}<0$$

Simple case with linear cost function in employment share

To provide a better understanding on the link between employment share and the HHI concentration measure, let's consider a linear cost function as follow:

$$C(W, N) = \frac{N}{\mathbf{N}} + W$$

where $\mathbf{N}$ is the total employment in the market. Therefore, the average optimal share of trainable and untrainable inputs ($\frac{\overline{T}}{\overline{U}}$) is:

$$\frac{\overline{T}}{\overline{U}} = \left[\frac{\alpha}{1-\alpha}\right]^{\alpha(\theta-1)} \left[\frac{(1+e(\overline{N}))C(W,\overline{N})}{\tau}\right]^{\alpha(\theta-1)} (1-\alpha)^{\theta}$$

where, given the assumed function of $C(W, N)$, we can re-write $(1 + e(\overline{N}))C(W, \overline{N})$ as

$$(1+e(\overline{N}))C(W,\overline{N}) = C(W,\overline{N}) + \frac{\partial C(W,\overline{N})}{\partial \overline{N}}\overline{N} = 2\frac{\overline{N}}{\mathbf{N}} + W$$

Given that $\overline{N}$ is the average employment in the market, it can be also written as $\sum_i s_i N_i$, where $s_i = {}^{N_i}/_{\mathbf{N}}$ is the share of employment employed by employer i

$$(1+e(\overline{N}))C(W,\overline{N}) = \frac{1}{\mathbf{N}^2}\sum_i s_i^2 + W = \frac{HHI}{\mathbf{N}^2} + W$$

Therefore, we can rewrite the average optimal share of trainable and untrainable inputs as:

$$\frac{\overline{T}}{\overline{U}} = \left[\frac{\alpha}{\tau(1-\alpha)}\right]^{\alpha(\theta-1)} \left[\frac{HHI}{\mathbf{N}^2} + W\right]^{\alpha(\theta-1)} (1-\alpha)^{\theta}$$

[28] Remember that the inverse labour supply elasticity is driven by the level of employment share, as an increase in the employment share increases the indirect cost of hiring/retaining workers.

Which leads to the following condition:

$$\frac{\partial \overline{T}/\overline{U}}{\partial HHI} \propto \frac{\alpha(\theta-1)}{\mathbf{N}^2}\left[\frac{HHI}{\mathbf{N}^2}+W\right]^{\alpha(\theta-1)-1} < 0$$

Representativeness of online vacancy data

As mentioned in the text a potential drawback of Omline Job Advertisements (OJAs) is that they may offer a biased representation of the entire universe of vacancies opening in a given country/region. Indeed Lovaglio et al. (2020) using time series decomposition and cointegration analyses, show that OJAs and official vacancies present similar time series properties, suggesting stocks of web job vacancies are reliable indicators of the true stocks of job vacancies. With the exception of the above mentioned paper assessing representativeness of OJAs for the specific case of Italy is not easy as the natural benchmark - official vacancy statistics - is not available. The Italian Statistical Office (Istat) in fact, publishes only the vacancy rate while the number of vacancies is kept confidential. In order to overcome this issue we have constructed two simple indicators. The first analyses the evolution over time (by quarter) from 2014 to 2019 of OJAs and of the vacancy rate which, albeit on a different scale, tallies very closely the number of vacancies posted. The second is derived from Labour Force Statistics. Using microdata from LFS we have identified positions filled in the last 3 months as a proxy of the number of vacancies. As vacancies signal positions open but not yet filled we have compared the LFS indicator with the lagged measure of OJAs. Also in this case we expect the scale of the two variables to be different while their time evolution to be similar. Figure F.3.6 shows that in both cases OJAs tally quite closely the evolution over time of both the vacancy rate and of recent hires (LFS) confirming that OJAs are a reliable indicator of the number of job openings in Italy.

G Extra Tables and Figures

G.1 Extra Tables

Table T.3.1: Correlation matrix between group 1 skill types

(a) Binary measure

	Skills	Knowledge	Ability	Activities	Styles
Skills	1				
Knowledge	0.316	1			
Ability	0.238	0.142	1		
Activities	0.374	0.443	0.170	1	
Styles	0.344	0.404	0.159	0.293	1

(b) TF-IDF measure

	Skills	Knowledge	Ability	Activities	Styles
Skills	1				
Knowledge	0.194	1			
Ability	0.0759	0.00602	1		
Activities	0.937	0.187	0.0629	1	
Styles	-0.0361	0.0386	-0.0223	-0.0728	1

Table T.3.2: Correlation matrix between group 2 skill types

(a) Binary measure

	Cognitive	HardSkills	Organizat	Social	Digital
Cognitive	1				
HardSkills	0.318	1			
Organizat	0.231	0.296	1		
Social	0.267	0.194	0.172	1	
Digital	0.381	0.415	0.110	0.206	1

(b) TF-IDF measure

	Cognitive	HardSkills	Organizat	Social	Digital
Cognitive	1				
HardSkills	-0.0345	1			
Organizat	0.0604	0.0442	1		
Social	-0.0248	-0.0377	-0.0119	1	
Digital	0.0246	0.0677	-0.0151	-0.0359	1

Table T.3.3: OLS estimates of labour market concentration on skill/competency demand (group 1), Binary measure across high and low skill occupations.

	Skill	Knowledge	Ability	Activities	Styles
GROUP 1, *Binary measure: High-skill occupations*					
log(HHI)	0.0036**	-0.0026**	0.0037***	0.0023*	0.0036**
	(0.0013)	(0.0009)	(0.0009)	(0.0010)	(0.0013)
MDV	0.519	0.851	0.115	0.798	0.636
mean(HHI*10k)	1,340	1,340	1,340	1,340	1,340
R^2	0.230	0.184	0.136	0.201	0.168
N	279,239	279,239	279,239	279,239	279,239
GROUP 1, *Binary measure: Low-skill occupations*					
log(HHI)	-0.0022*	-0.0047***	0.0002	0.0010	-0.0020
	(0.0009)	(0.0011)	(0.0004)	(0.0011)	(0.0012)
MDV	0.142	0.555	0.024	0.550	0.392
mean(HHI*10k)	1,298	1,298	1,298	1,298	1,298
R^2	0.092	0.358	0.053	0.361	0.136
N	273,788	273,788	273,788	273,788	273,788

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the binary measure of the broader skill classification (group 1) described in section 3.4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions include year, province, industry, and occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table T.3.4: OLS estimates of labour market concentration on skill/competency demand (group 2), Binary measure across high and low skill occupations.

	Cognitive	Hard Skills	Organizational	Social	Digital
GROUP 2, *Binary measure: High-skill occupations*					
log(HHI)	0.0020	0.0038**	0.0026*	0.0060***	0.0028**
	(0.0013)	(0.0013)	(0.0011)	(0.0012)	(0.0011)
MDV	0.540	0.550	0.211	0.532	0.287
mean(HHI*10k)	1,340	1,340	1,340	1,340	1,340
R^2	0.258	0.222	0.163	0.293	0.348
N	279,239	279,239	279,239	279,239	279,239
GROUP 2, *Binary measure: Low-skill occupations*					
log(HHI)	-0.0012	0.0028**	-0.0031***	0.0002	-0.0013*
	(0.0010)	(0.0011)	(0.0004)	(0.0010)	(0.0006)
MDV	0.162	0.275	0.030	0.381	0.056
mean(HHI*10k)	1,298	1,298	1,298	1,298	1,298
R^2	0.096	0.220	0.093	0.462	0.107
N	273,788	273,788	273,788	273,788	273,788

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the binary measure of the finer skill classification (group 2) described in section 3.4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions include year, province, industry, and occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table T.3.5: OLS estimates of labour market concentration on skill/competency demand (group 1), TF-IDF measure across high and low skill occupations.

	Skills	Knowledge	Ability	Activities	Styles
GROUP 1, *TF-IDF measure: High-skill occupations*					
log(HHI)	0.0003	-0.0007***	-0.0005	0.0004	0.0001
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
MDV	0.073	0.052	0.022	0.067	0.065
mean(HHI*10k)	1,340	1,340	1,340	1,340	1,340
R^2	0.319	0.290	0.019	0.267	0.122
N	279,239	279,239	279,239	279,239	279,239
GROUP 1, *TF-IDF measure: Low-skill occupations*					
log(HHI)	0.0013	-0.0011	-0.0000	0.0008	0.0019*
	(0.0007)	(0.0007)	(0.0003)	(0.0007)	(0.0008)
MDV	0.127	0.114	0.012	0.122	0.142
mean(HHI*10k)	1,298	1,298	1,298	1,298	1,298
R^2	0.079	0.093	0.014	0.076	0.086
N	273,788	273,788	273,788	273,788	273,788

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the tf-idf intensity measure of the broader classification (group 1) described in section 3.4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions include year, province, industry, and occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table T.3.6: OLS estimates of labour market concentration on skill/competency demand (group 2), TF-IDF measure across high and low skill occupations.

	Cognitive	HardSkills	Organizat	Social	Digital
GROUP 2, *TF-IDF measure: High-skill occupations*					
log(HHI)	-0.0001	0.0005	0.0004	0.0003	-0.0004
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0002)
MDV	0.073	0.070	0.031	0.050	0.029
mean(HHI*10k)	1,340	1,340	1,340	1,340	1,340
R^2	0.071	0.099	0.055	0.069	0.050
N	279,239	279,239	279,239	279,239	279,239
GROUP 2, *TF-IDF measure: Low-skill occupations*					
log(HHI)	-0.0011	0.0018**	-0.0014***	0.0015**	-0.0005
	(0.0007)	(0.0007)	(0.0002)	(0.0005)	(0.0002)
MDV	0.079	0.108	0.012	0.070	0.019
mean(HHI*10k)	1,298	1,298	1,298	1,298	1,298
R^2	0.027	0.065	0.048	0.098	0.055
N	273,788	273,788	273,788	273,788	273,788

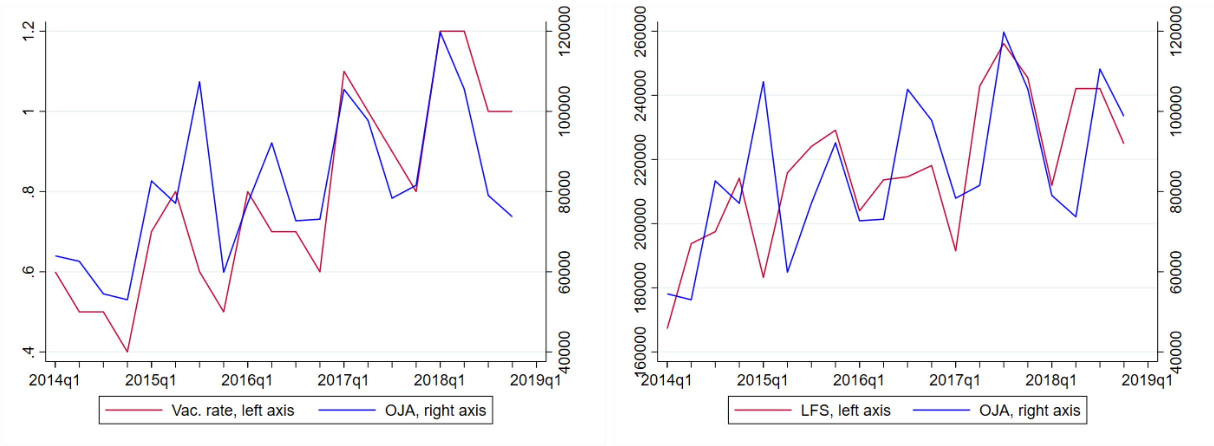
Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the tf-idf intensity measure of the finer classification (group 2) described in section 3.4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions include year, province, industry, and occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

G.2 Extra Figures

Figure F.3.6: Online vacancies and official statistics

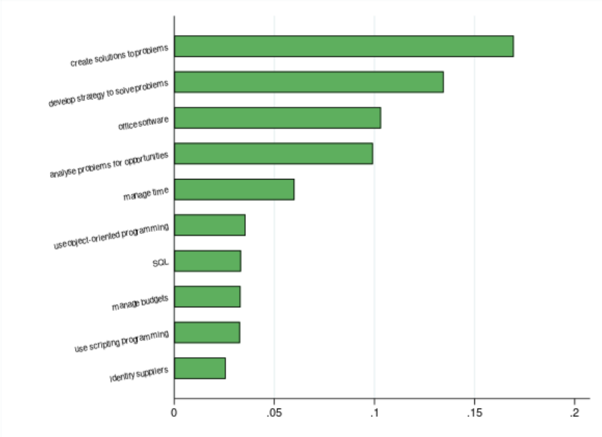
(a) Online vacancies and official vacancy rate (b) Online vacancies and LFS recent hirings



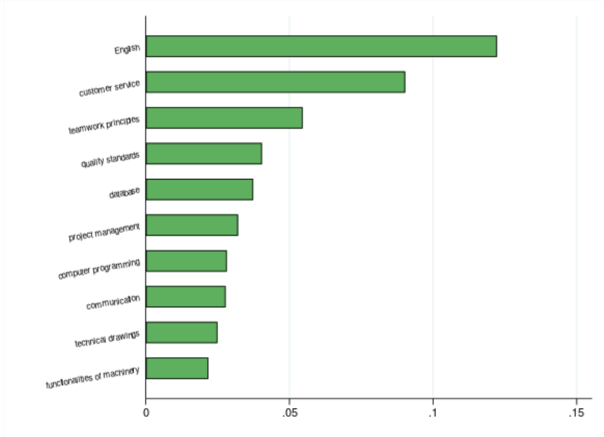
Authors' calculations Istat and WollyBi data of 2014-2018. LFS data refer to recent hirings (those who found a job in the last 3 months).

Figure F.3.6: Description top10 competencies for group 1

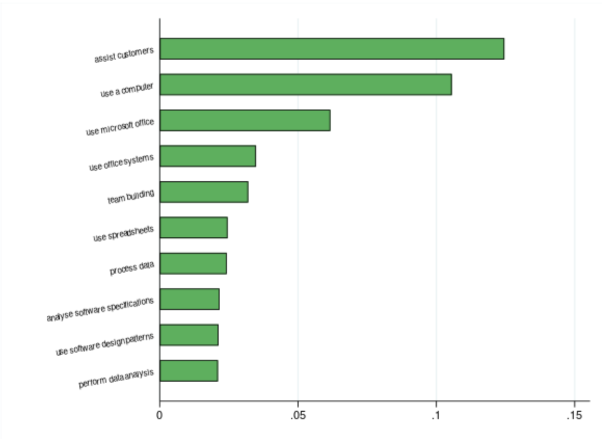
(a) Skills



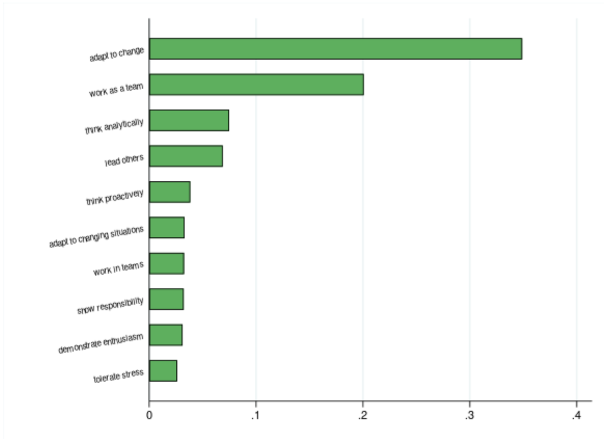
(b) Knowledge



(c) Activities



(d) Styles



(e) Ability

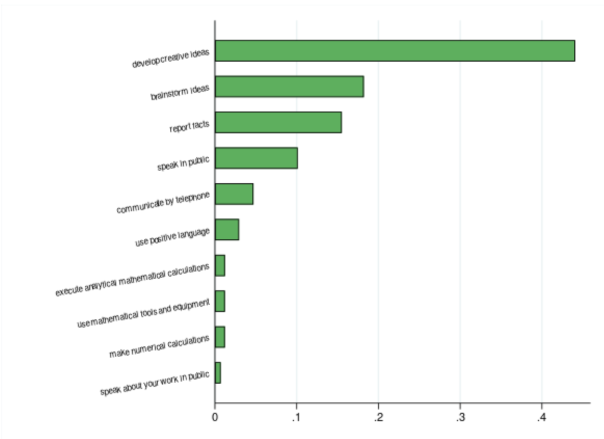
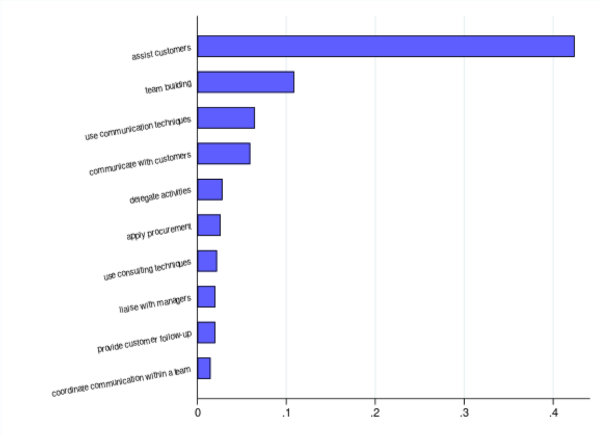
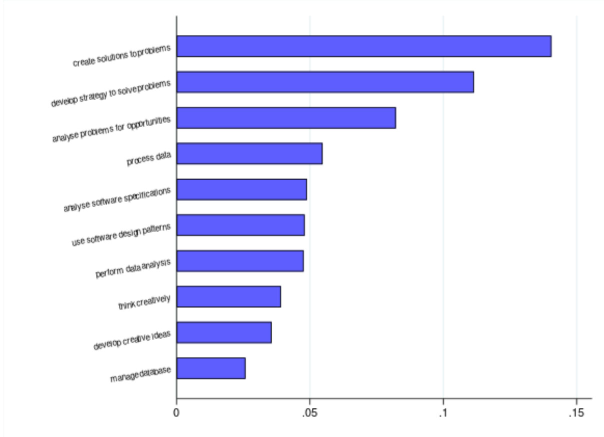


Figure F.3.6: Description top10 competencies for group 2

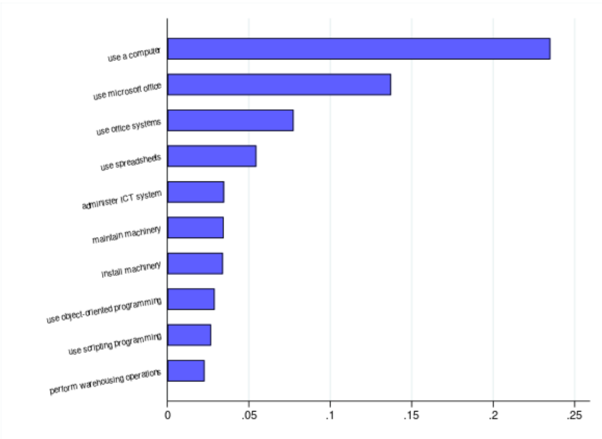
(a) Social



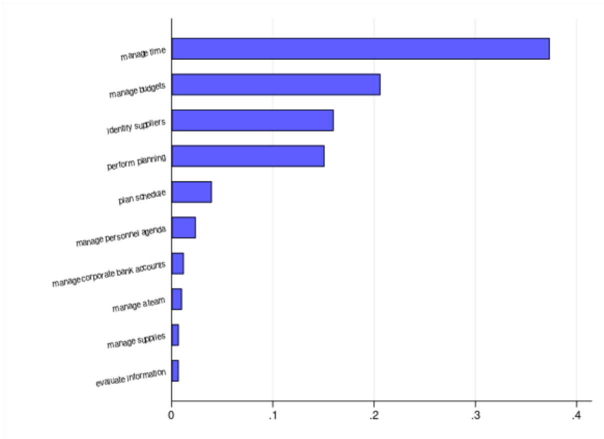
(b) Cognitive



(c) Hard Skills



(d) Organizational Skills



(e) Digital Skills