Workplace Training Unpacked: Labor Market Competition and Investment in General Skills

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Abstract

Skills acquired on the job, whether general or specific, significantly influence workers' labor market outcomes. Workers with general skills tend to have higher re-employment prospects and greater resilience to economic shocks. Using novel data from two different policy interventions in the Italian labor market, we develop a new measure that captures the generality of the tasks taught in firm-provided training for individual workers. This measure enables us to examine the relationship between labor market competition and the nature of firms' human capital investment. Our findings indicate that, as theory predicts, workers in more competitive labor markets receive less general training.

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1 Introduction

Workforce training is crucial for firms to enhance human capital and adopt new technologies. However, the provision of training by employers faces hold-up problems: firms cannot fully capture the returns on their investment because the workers, in whom the training is embedded, can be poached by competitors. The existing theoretical literature suggests that imperfectly competitive labor markets can be conducive to more general training (Acemoglu and Pischke 1998; Moen and Rosén 2004). Despite this, an empirical test of this mechanism remains absent. The primary obstacle to such analysis is the scarcity of firm-level data on training, particularly regarding the specific skill content of the training projects in which firms invest. Indeed, previous studies have primarily focused on how competition and turnover affect the decision of *whether* to train. In this paper, we explore a different mechanism: firms may mitigate the risk of losing employees to competitors by providing specialized skills that are less transferable to other firms in the market.

Recent evidence indicates that the type of skills acquired on the job has a lasting impact on workers' labor market outcomes (Adda and Dustmann 2023; Macaluso 2023; Eckardt 2023 Caldwell and Danieli 2024). Workers with general skills can easily transition between industries, making them more resilient to economic shocks. In contrast, high levels of industry-specific knowledge increase mobility costs and hinder transitions across sectors. This is why moving between industries can be exceedingly costly (Yi et al. 2024, Andrieu et al. 2019), even if such transitions could be socially beneficial, as they enable workers to relocate to firms where they can be more productive or enjoy better working conditions. Furthermore, novel literature (Citino et al. 2023) has shown that the workers who are most affected by industry-level shocks are those with the lowest potential for reallocation to other industries. Therefore, it is crucial to explore whether labor market policies can alleviate these challenges by equipping workers with the skills necessary to enhance their resilience.

In this paper, we empirically investigate the relationship between labor market competition and the type of training investments made by employers. Specifically, we create a novel worker-level dataset exploring the information from two recent policies enacted in the Italian labor market to examine how local labor market competition affects firms' propensity to invest in general versus specific skills. The granularity of the data we collect allows us to observe all training courses attended by each worker, and map each skill learnt into the industry it is used the most. Crucially, we are the first to measure the generality of training content by analyzing the specific tasks taught in each program, rather than relying on firm-level surveys.

The first policy we examine is the first edition of the *Fondo Nuove Competenze* (FNC), launched by the Italian Government in 2020 and implemented from 2021 onward. Using detailed information from policy applicants, we construct a new measure of training content generality at the worker level and match it with administrative data from various sources. Based on the governmental definition of general training, we calculate a worker-specific generality score of the received training as an hour-weighted average of the courses attended. This enables us to address our primary research question on the effect of labor market competition on firms' training decisions and to provide fresh insights into the effectiveness and labor market impact of a recent policy experiment in a large industrialized economy.

In the second part of the paper, we expand our analysis by examining data from an earlier policy. Specifically, we leverage information from *Fondimpresa*, the largest Italian inter-professional fund and the primary source of public funding for the development of workplace development programs. The availability of a repeated cross-sectional dataset allows us to analyze how training content has evolved over time and identify exogenous variation in local labor market competition. In particular, we draw from the literature on shift-share IVs (Goldsmith-Pinkham et al. 2020) and construct a new instrumental variable for the poaching risk that firms in a given local market face. Also in this case, we estimate

a negative effect of exposure to poaching risk on the provision of general training. Hence, this additional exercise corroborates the evidence produced in the first part of the paper.

Italy offers a compelling context for addressing our research question for several reasons. First, the local nature of its labor market provides significant variation to examine establishments exposed to different levels of local labor market competition. Second, Italy faces challenges in developing human capital across its adult population. Over 50% of Italian adults possess potential for upskilling, characterized by low levels of education, digital skills, cognitive skills, or a high risk of skill loss and obsolescence.[1] Despite this, fewer than 40% of adults engage in any form of educational or training activity.[2]

While *hold-up* frictions undoubtedly contribute to low training uptake and effectiveness, it is often difficult to disentangle demand from supply effects. Training provision may enhance a firm's attractiveness to incoming workers, making it harder to isolate the effect of competition on the type of training provided by firms from any strategic choice to attract workers. The *FNC* data enables us to tackle this issue, as firms must commit to the specific workers they will train when they apply for funding. This requirement allows us to focus our analysis on the training of existing workers, effectively controlling for the relationship between training and competition in the hiring market. At the same time, training could be used by firms as a tool to retain existing workers, as it could be considered as a form of non-wage compensation. This force goes in the opposite direction to the *hold-up* channel, as workers in more competitive labor markets will require higher non wage compensation. In this paper, we are able to establish which of these two channels empirically dominates.

To determine the impact of labor market competition on the type of training provided, we develop a theoretical model of firms' training content choices. This model incorporates the decisions firms make regarding the type of training they offer, as well as the mobility of

[1] https://www.inapp.gov.it/wp-content/uploads/2023/01/CEDEFOP-Empowering-adults-I_0.pdf

[2] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Adult_learning_statistics

workers across firms and industries.

We apply this model to our unique dataset and test its predictions. To control for potential heterogeneity at the firm level, we employ fixed effects at both the firm and firm-occupation levels, effectively restricting our analysis to a sub-sample of multi-establishment firms. By comparing similar workers employed in the same firms but located in geographically distinct establishments with varying levels of local market competition, we can isolate the effect of increasing the number of competitors in a given market on the generality of workers' training content. In the *Fondo Nuove Competenze* sample, we find that increasing by one standard deviation (1 percentage point) the share of local establishments in other industries lowers training content generality by approximately 5% with respect to the mean. We also find that the same variation leads to a 6% decrease in the probability that a worker receives some general training. We find similar results in the sample from *Fondimpresa*. Here, a similar increase in the poaching risk that firms face lowers training content generality by approximately 6%. These estimates suggest that firms mitigate hold-up risks by providing their workers with industry-specific skills. We take this as evidence that labor market competition lowers the provision of general training below the socially-optimal level.

Our findings speak to different strands of literature and are consistent with predictions from economic theory. As noted by Arrow 1962, a significant portion of learning occurs on the job. This reality has prompted economic theory to focus extensively on the determinants of training provision by firms. Since Becker's seminal work (Becker 1962), economists have framed training provision as a hold-up problem. The key insight from Becker's analysis is that, in perfectly competitive labor markets, firms are unlikely to invest in general skills at all. Subsequent research has highlighted that in imperfectly competitive labor markets, firms may find it profitable to invest in workforce training, provided they can appropriate a sufficiently large share of workers' marginal product. As Acemoglu and Pischke 1999 points out, this occurs when distortions compress the wage structure, such as monopsony power

(Manning 2013, Dustmann and Schönberg 2002) or informational asymmetries (Autor 2001). A related strand of the theoretical literature has examined the differences and implications of general versus firm-specific or industry-specific training. Smits 2007 is the first paper, to our knowledge, to distinguish explicitly between fully generic and industry-specific skills and to develop a theory regarding firms' investment in these two types of training. Seminal work by Stevens 1994, Lazear 2009 and Gibbons and Waldman 2004 emphasized that the degree to which a skill is classified as general or specific depends on the market's thickness for that particular skill.

Despite the significant theoretical interest, empirical research on the relationship between labor market competition and training provision by firms remains limited. Brunello and Gambarotto 2007 and Brunello and De Paola 2008 find that, both in Italian and British contexts, firms located in denser markets and areas with higher labor market competition tend to invest relatively less in general training. Conversely, recent work by Marcato 2022 reveals that Italian firms in concentrated labor markets provide, on average, more training to their employees. Similar results have also been reported by Morin and Védrine 2022 for French firms and by Mohrenweiser et al. 2019 in the context of the German apprenticeship system. Our research complements the existing evidence in two key ways. First, our measures of training content generality are based on observational data rather than surveys (Loewenstein and Spletzer 1999; Starr et al. 2018; Dietz and Zwick 2021) or experimental data (Adhvaryu et al. 2018), enabling us to directly map training courses to the industries where the skills taught will be applied. Second, we are the first to empirically analyze how firms, conditional on providing training, can strategically adjust the training content based on the level of competition they face.

Our results also contribute to the applied literature that, independent of competition, seeks to assess the returns for firms and workers from various types of training investments (Loewenstein and Spletzer 1999, Konings and Vanormelingen 2015, Adhvaryu et al. 2018,

Alfonsi et al. 2020, Bianchi and Giorcelli 2022, Bentolila et al. 2023). We offer novel evidence on the outcomes of a significant labor market intervention aimed at upskilling the existing workforce, rather than focusing solely on integrating young workers. Our findings suggest that firm-side policies can effectively enhance the redeployability of adult workers, particularly when labor market competition is low and firms provide sufficient general skills training. At the same time, our results indicate that firms located in more competitive labor markets adjust their training content to mitigate the costs associated with employee turnover. Additionally, the granularity of our data, combined with both firm-level and worker-level information, allows us to examine how labor market competition interacts with other determinants of training provision, such as workers' preferences (Caliendo et al. 2023), managerial frictions (Adhvaryu et al. 2023), and technological shocks (Lipowski et al. 2024).

This paper also contributes to the growing literature in organizational economics concerning firms' internal allocation of talent and skills (Bassi et al. 2022, Bassi and Nansamba 2022, Caicedo et al. 2022). In particular, our results relate to the literature on job reallocation for workers affected by shocks and the dynamism in the labor market (Davis and Haltiwanger 1999, Citino et al. 2023, Barbieri et al. 2022), as the policy we examine aims to improve the resilience and reallocative potential of recipient workers. Moreover, our findings are complementary to recent evidence for developing countries: Cefala et al. 2024 show that, in the context of informal agriculture in Burundi, firms concentrate their training investments in workers with long-term contract, thus confirming that hold-up frictions influence firms' training strategies.

Ultimately, we enhance the expanding literature on labor market competition and power (Berger et al. 2022, Benmelech et al. 2022, Azar et al. 2022), by considering an alternative channel through which competition can impact workers' outcomes.

The remainder of the paper is organized as follows: Section 2 presents the theoretical model to convey the primary intuitions behind the mechanisms we test. Section 3 contains

the empirical analysis and descriptive evidence concerning the first policy we study, the *Fondo Nuove Competenze*; Section 4 details the quasi-experimental analysis conducted on the *Fondimpresa* data; and Section 5 concludes the paper while outlining potential avenues for future research.

2 Conceptual Framework

Before entering the core of the empirical analysis, we lay out a simple theoretical model of firms' investment in general versus specific training. The model will inform us on how we should expect labor-market competition to influence firms' choice of training content generality. Our model incorporates both firms' choice of investing in two different types of training, general or industry-specific, as in Stevens 1994 and Smits 2007, and workers' mobility choice, as in Card et al. 2018.

2.1 Model Set-up and Assumptions

Production requires one firm and one worker: output is a function of the worker's endowment of two different human capital types, namely *fully-general* human capital g, that can be used at all firms in the market, and *industry-specific* human capital s, that is useful only within a given class of firms. Hence, a firm's final output is $Q = f(g, s)$, where $f(g, s)$ is the production function, which is such that $\frac{\partial f(g,s)}{\partial g} > 0$ and $\frac{\partial f(g,s)}{\partial s} > 0$. Training is costly, according to some convex cost $c(g, s)$ borne by firms.

Each worker i is born initially at some firm j, in industry $S(j)$. The firm can choose how much to train the worker in both types of human capital; in a second period, the worker can choose whether to move to another firm. In particular, workers are heterogeneous in terms of a taste-shock ϵ_{ij}, that they draw at the beginning of the second period: this shock disciplines j's decision of whether to stay in firm j, or move to any other firm.

Mobility decisions are also (endogenously) affected by a worker's human capital endowments. In fact, whenever a worker moves within her original industry, she preserves both her general and industry-specific skills and produces $f(g, s)$. Workers that switch industry, instead, will carry with them only general human capital and produce $f(g, 0)$.

2.2 Labor Supply

Worker i's utility, when employed at j, can be written as:

$$u_{ij} = \beta w_{ij} + \epsilon_{ij}$$

where w_{ij} is the wage paid by the firm at the end of the production process, $\beta \geq 0$ is the parameter regulating workers' wage elasticity of labor supply, which in this paper we assume to be constant across workers. Moreover, we assume that $w_{ij} = \alpha f(g, s)$, where $\alpha \in [0, 1]$ is workers' bargaining weight, also constant across firms and workers.

Given these preferences, worker i will prefer working at j over k if:

$$\alpha\beta f(g, s) + \epsilon_{ij} > \alpha\beta f(g, s) + \epsilon_{ik}, \text{ if } S(j) = S(k)$$

$$\alpha\beta f(g, s) + \epsilon_{ij} > \alpha\beta f(g, 0) + \epsilon_{ik}, \text{ if } S(j) \neq S(k)$$

Under the assumption that $\epsilon_{ij} \sim$ Type 1 Extreme Value, the probability that a worker stays at the original firm is:

$$\begin{aligned}\mathbb{P}(u_{ij} \geq u_{ik}, \forall k \neq j) &= \pi_{ij}(g, s; N_k, N_\rho) \\ &= \frac{exp[\beta\alpha f(g, s)]}{\sum_{k \in S(j)}^{N_k} exp[\beta\alpha f(g, s)] + \sum_{\rho \notin S(j)}^{N_\rho} exp[\beta\alpha f(g, 0)]}\end{aligned}$$

This expression can be re-written as follows, using $\beta\alpha = \gamma$ and firm symmetry:

$$\pi_{ij}(g, s; N_k, N_\rho) = \frac{exp[\gamma f(g, s)]}{N_k exp[\gamma f(g, s)] + N_\rho exp[\gamma f(g, 0)]} \tag{1}$$

where N_ρ is the number of firms in other industries, N_k is the number of firms in the same industry as j.

2.3 The Firm's Problem

In the first period, firms choose how much to invest in g and s, subject to the investment cost $c(.)$, so to maximize their profits:

$$\max_{g,s} \ \pi_{ij}(g, s; N_k, N_\rho)(1-\alpha)f(g,s) - c(g,s) \tag{2}$$

Take the FOCs:

$$[g]: \frac{\partial \pi(g,s)}{\partial g}(1-\alpha)f(g,s) + \pi(g,s)(1-\alpha)\frac{\partial f(g,s)}{\partial g} = \frac{\partial c(g,s)}{\partial g}$$
$$[s]: \frac{\partial \pi(g,s)}{\partial s}(1-\alpha)f(g,s) + \pi(g,s)(1-\alpha)\frac{\partial f(g,s)}{\partial s} = \frac{\partial c(g,s)}{\partial s}$$

Under the additional assumption of separability of the production function ($\frac{\partial f(g,s)}{\partial g \partial s} = \frac{\partial f(g,s)}{\partial s \partial g} = 0$) in the two inputs, the ratio of the FOCs can be re-written as:

$$\frac{f_g}{f_s}\frac{1}{1+\gamma f \Omega} = \frac{c_g}{c_s} \tag{3}$$

where f_x, c_x are the partial derivatives of f and c w.r.to input $x \in (g, s)$, and

$$\Omega = \frac{N_\rho exp(\gamma f(g,0))}{N_\rho exp(\gamma f(g,0)) + N_k exp(\gamma f(g,s))} \tag{4}$$

Notice that Ω is a number between 0 and 1 and it is weakly increasing in N_ρ and weakly decreasing in N_k. The full derivation of equation (3) is included Appendix section A.2.

2.4 Comparative Statics

For simplicity, we impose the further assumption that the production function is linearly additive and separable in the two types of training $f(g,s) = ag + bs$, and that the cost

function is quadratic and separable $c(g,s) = \kappa_g g^2 + \kappa_s s^2$, we can re-write equation (3) as:

$$\frac{g}{s} = \frac{\kappa_s}{\kappa_g} \frac{a}{b\left[1 + \gamma(ag + bs)\Omega\right]} \tag{5}$$

If the objective function is concave, the system of the first order conditions identifies a solution to the firm's problem. In Appendix Section A.3, we show for which values of the parameters the profit function admits a global maximum. When this is the case, we can use equation (5) to study comparative statics with respect to the parameters that capture the extent of competition from inside a firm's indsutry and from outside, namely N_k and N_ρ. Firms will determine the share of general to specific training $\frac{g}{s}$ by weighting: (i) the ratio between the marginal costs of the two investments $\frac{\kappa_g}{\kappa_s}$, (ii) the ratio of their marginal products $\frac{a}{b}$ and (iii) the wedge $\frac{1}{1+\gamma f \Omega}$. *Ceteris paribus*:

- a rise in N_ρ **lowers** the relative gain from providing general training (because it increases Ω)
- a rise in N_k **increases** the relative gain from providing general training

The main goal of the model is to guide the formulation of hypotheses that can be tested in the data.

Given the comparative statics listed above, the model suggests the following empirical strategy: compare two firms A and B, located in different local labour markets, such that $N_{\rho,A} \geq N_{\rho,B}$ and $N_{k,A} = N_{k,B}$. If A and B share the same technology $f(g,s)$ and $c(g,s)$, then we should expect A to provide less general training than B.

In practice, such a direct comparison cannot be done, as a firm's technology and training cost are unobservable. In the following sections, we will show how we can use fixed effects and unique features of our data to identify the relevant comparisons.

3 Analysis on Fondo Nuove Competenze Data

3.1 Institutional Framework and Data

In May 2020, the Italian Government established a new fund, named *Fondo Nuove Competenze* (FNC), to issue grants for firms that wanted to invest in the upskilling of their workforce[3] through the National Agency for Active Labor Policies (ANPAL). The fund was part of the measures taken by the government to alleviate the consequences of COVID-19 and to improve firms' resiliency. As stated in the joint decree issued by the Ministry of Work and Social Policies and the Ministry of Finance, the primary goal of the policy was to finance the acquisition of "new skills, motivated by the introduction of organizational, technological, process or product innovations, or in response to changes in firms' productive needs", but also "to boost the reallocation potential of workers, in order to promote mobility to alternative workplaces".[4]

The application period lasted from February 2021 to June 2021. All eligible applicant firms received funding, as the only eligibility criterion for firms was to not have any ongoing legal proceedings. FNC issued grants for 2.3 billion euros to 12,213 recipient firms, funding training programs for 637,159 workers. This corresponds to approximately one third of the overall training expenditure of Italian firms.[5] The lack of criteria on content and type of workers allowed firms to freely optimize their training strategy, thus creating a unique context where the training funded encompassed several types of tasks and any worker along the corporate hierarchy. In terms of funding, FNC reimbursed firms for the labor cost corresponding to the hours each worker spent on training, rather than financing the training

[3] law-decree n.34, May 19 2020, article 88

[4] Interministerial Decree of October 9, 2020, Article 3.2: https://www.anpal.gov.it/documents/552016/586402/D.I.del22ottobre2020-FondoNuoveCompetenze.pdf/f1d4df92-7b56-4f65-2993-438954f591bb?t=1611054899893

[5] According to the estimates of the 2020 Continuous Vocational Training Survey, Italian firms spent approximately 6.2 billion euros in training costs: https://www.istat.it/tavole-di-dati/la-formazione-del-personale-nelle-imprese-per-regione-anno-2020/

programs directly.

3.2 Data

We use application-level data comprising all recipient firms that have successfully completed the training programs. The raw data consists of 8,752 firms and 343,601 recipient workers. We combine data on training programs with firms' balance sheet information and workers employer-to-employer (E to E) transition records to build our dataset.

Worker & Training Data

We obtain both worker-level information and the individual training certificates of all the workers in our sample from ANPAL. These data include firm and workers' *codice fiscale* (social security number), municipality of the establishment, age, gender, contract type, contract duration, and workers' hierarchical position within the firm. We use the training certificates to reconstruct the content and duration of each class workers attended. The content is defined in terms of ADA[6] codes. The FNC Call for Applications explicitly demanded firms to include in each certificate the ADA code (or codes) associated with the tasks taught. Each code maps a course into a specific task and the industrial sector where this task is performed, as specified by the *Work Atlas* of Istituto Nazionale per le Analisi delle Politiche Pubbliche (INAPP). Table 1 provides an example of two codes. A full map of all the relevant sectors, and how they map into the ADA codes used for the certificates is available on INAPP's webpage.[7]

The first activity presented in Table 1 is "Opening of wool flocks", described by code 05.01.06. In any six-digits code the structure is common:

- The first two digits characterize the industry where a certain training activity is rel-

[6] ADA stands for Italian "*Aree di attività*", literally "Areas of activities"
[7] https://atlantelavoro.inapp.org/

Sector	Process	Sub-Process	Activity	Description
05				Textile
	01			Textile production
		03-07		Preparation of spinning fibers
			05.01.06	**Opening of wool flocks**
24				Common Area
	05			Management of production
		01-05		Production planning and control
			24.05.03	**Project management**

Table 1: ADA code examples

evant: this corresponds to first digit of the Italian ATECO industry classification, comparable to the first two digits in the SIC classification;

- the second and third couples correspond to the process and sub-process of the training activity.

There are only two exceptions to this classification. The first is when the code 24 is used in the first two digits, corresponding to all activities that are *common* across many firms (e.g. "project management", as in Table 1). The second is when the code is missing, corresponding to soft skills[8] training. Indeed, ANPAL allowed firms to not report any ADA code if programs were trainign soft skills. Hence, we classify the cases of missing ADA codes as belonging to no specific industry (00.00.00).

Firms' Balance Sheet Information

Our source for firm-level balance sheet data is the AIDA[9] dataset, which contains digitized balance sheets for about 1.3 million Italian limited-liability firms from 2012 to 2021. This dataset has information on firms' employment, labor cost, value added, capital, profits, and industry. We use firms' *codice fiscale* to match 8,082 firms and 331,085 workers from the

[8] soft-skills include public speaking, team building activities and language courses
[9] Analisi Informatizzata delle Aziende Italiane

training dataset to financial information on firms' headquarters. The unmatched observations can be ascribed to non limited-liability firms, which are not included in the AIDA data. We will use this information to control for firms' characteristics and understand what firm-level factors drive differences in training content choices.

Local Labour Market Characteristics

We derive the information on local labour markets characteristics from the 2021 version of the ASIA-ULP (the statistical register of local establishments of ISTAT, the Italian National Statistical Institute). This dataset includes municipality-level information on the number of workers and number of establishments by industry.

Workers' E to E Flows

Using workers' social security numbers, ANPAL matched the sample of trained workers to the *Comunicazioni Obbligatorie* dataset: these data record any contractual change that happened within and across firms from 2009 to the beginning of 2024 and provides us with additional information on the occupation of such workers. For the first transition after the end of the training, we also know the identity and the industry of the recipient firm. We match 252,784 workers to this dataset: unmatched workers are those whose contract did not experience any reported change since 2009. We include the unmatched workers in most of the analysis that follows, with the exception of regressions in which we use occupation as an additional control.

3.3 Descriptives

In this section, we exploit the granularity of the data collected to answer questions on who are the firms and the workers that participated to the first edition of the *Fondo Nuove*

Competenze - from now on FNC firms -, and how they differ from the rest of the firms in the Italian Economy.

Firms

The first panel of Table 2 reports some key summary statistics for the balance-sheet variables that we obtain via the match to AIDA. Interestingly, FNC firms train through the policy a large share of the total workforce: the median share of workers trained is 70%. In terms of their size, FNC firms are sizeably larger than the average Italian firm: Table 2 reports key moments of the distribution of several measures of firm size, namely the logarithm of sales, the number of employees and the log of total capital. The bottom row in Table 2 reports, for each variable, the difference in means from the rest of firms in the Italian economy. Not only FNC firms are larger, but they are also more profitable and have higher labor costs.

	ln Sales	**ln V. Added**	**ln Employees**	**ln Labor Cost**	**ln Capital**	**ln Profits**	**Sh. Trained**
FNC Sample:							
Mean	7.966	6.905	3.130	6.524	6.058	4.433	0.645
Std. Dev.	1.709	1.561	1.317	1.539	2.471	2.103	0.274
All Firms:							
Mean	5.724	4.553	1.630	4.282	4.195	3.002	0.000
Std. Dev.	2.012	1.969	1.198	2.260	2.685	2.043	0.000
Difference	2.242***	2.351***	1.500***	2.242***	1.863***	1.431***	
	(0.023)	(0.023)	(0.014)	(0.026)	(0.031)	(0.025)	

Table 2: The table shows summary statistics of the main balance-sheet variables used in the analysis for FNC firms and the rest of Italian firms. Monetary variables are measured in millions of Euros.

Table 2 shows that FNC firms are larger than the average firm in the Italian economy. This confirms a general pattern, which we document next. In Figure 8, we plot the distribution of log sales for FNC firms and for training and non-training firms derived from a 2018 INAPP survey on firms and labor.[10] The figure suggests that the FNC sample is representative of the population of training firms in Italy.

[10]INAPP is the Italian National Institute for the Assessment of Pulic Policies: https://www.inapp.gov.it/rilevazioni/rilevazioni-periodiche/rilevazione-imprese-e-lavoro-ril

As shown in Figure 9, recipient firms span a large number of industrial sectors, defined according to the taxonomy provided by INAPP's *Work Atlas*[11]: the largest number of firms operates in manufacturing, in the construction sector and in wholesale and retail trade. We will stick to this taxonomy for the rest of the Section, as this will be the same used by FNC firms to classify their training activities. Compared to the rest of firms in the Italian economy, the FNC sample tilts towards Manufacturing, and displays less firms in Wholesale and Retail, in Construction and in the Hotel and Catering sectors. The difference is due to the fact that, in these sectors, the average firms tends to be smaller, and, as shown in Figure 8, small firms are less inclined to provide training to their employees. FNC firms are evenly distributed across the Italian territory, with a slight prevalence of Southern regions. When considering the distribution of workers across locations, however, Northern regions display more participants: that is because the average firm size in the North is larger than in the South (Figure 10).

Workers

Looking at the workers trained through the *Fondo Nuove Competenze*, our sample is characterized by large heterogeneity, along multiple dimensions: occupation, the hierarchical position within the firm, the duration and the type of contract awarded to each worker, and demographics (age and gender).

The first column of Table 3 shows the number of workers in each hierarchical layer, column 2 the number for each contract type, and column 3 for each contract duration span. Most of the trained workers are either production workers or clerks, with full-time permanent contracts: this is consistent with what theory suggests (Becker 1962, Stevens 1994), as firms should not train their workers if they expect them to leave.

In terms of demographics, 36% of our sample is made up by female workers. The average

[11] https://atlantelavoro.inapp.org/atlante_lavoro.php

Hierarchy		Contract Type		Contract Duration	
Apprentice	12,524	Full-time	265,702	Permanent	319,296
Production worker	125,569	Part-time	72,185	Temporary	17,882
Clerk	171,227			Seasonal	709
Middle manager	21,705				
Top manager	3,261				
Other	546				

Table 3: Contract-level characteristics of trained workers

worker is 44 years old. Appendix Figure 12 reports the age distribution of the workers of our sample by gender.

3.4 Measurement of Training Content Generality

In this subsection, we will discuss in detail how information contained in training certificates can be used to obtain the training content type to which each worker has been exposed. In particular, we will construct two different measures capturing the relative prevalence of **general** over **industry-specific skills**. The first measure is the share of the total training hours that have been devoted, for each individual, to learning general skills, as opposed to industry-specific skills: for the rest of the analysis, this will be referred to as the *General Intensity* of each worker. The second measure is a **discrete** version of the first, namely an indicator equal to one for each worker that has been exposed to *at least one* hour of general training, and equal to zero otherwise. We will refer to this measure as the *Generality Indicator*.

Based on the definition of sectors provided by the INAPP *Work Atlas*, we define as general any training program belonging to the ADA sector 24 or with no indication of the ADA code. All other ADA sectors are considered industry-specific.
We extract from each training certificate the set of codes using the Tesseract OCR engine. This process allows us to estimate the precise training content for 242,008 workers. As

shown in the Appendix, all the results obtained throughout the paper are robust to excluding ADA = 0 from the definition of general training. Appendix Figure 13 plots the empirical distribution of the first two digits ADA codes in our data: more than half of all training is general (the sum of columns 0 and 24); in the industry-specific training group, instead, the largest fraction of courses happens in the Manufacturing sector, in Digital Services and in Wholesale and Retail Trade. Some workers (56,903) participated in at least one industry-specific class that did not match their employer's industry code. In our baseline analysis, we still treat these forms of training as industry-specific. However, we repeat the whole analysis, excluding these courses. As shown in Appendix Section A2, these changes do not affect our final results.

We use our generality measures to compute the intensity of training in general skills for worker j, taking a weighted average across all the courses k they attend:

$$Gen.Intensity_j = \frac{\sum_k \mathbb{I}(ADA_{jk} = 24 \; or \; ADA_{jk} = 0) \times Duration(ADA_{jk})}{\sum_k Duration(ADA_{jk})}$$

Similarly, we compute the *Generality Indicator* using the following formula:

$$\mathbb{I}(General_j) = \mathbb{I}(Gen.Intensity_j > 0)$$

Figure 14 plots the distribution of the two measures described above. Both are bounded on the [0,1] interval, with two mass points at the extremes. Given the way it is constructed, the General Intensity measure also displays some mass for intermediate values. The two measures will be the two main outcome variables for the empirical analysis in the next section.

Table 4 reports how the two measures differ across workers with different observable

characteristics. On average, female workers receive relatively more general training than male workers, most likely due to the differences in the occupational composition between male and female workers. Interestingly, older workers receive more general training. One possible explanation is that older workers are more likely to perform managerial tasks, which are more general in nature (this is also shown in Table 4, Panel C). A second possible explanation is that older, high-tenure workers are less likely to leave the firm, hence less subject to *hold-up* considerations. There is also substantial variation across occupations, as shown in Panel D: executives and intellectual professions receive more general training, whereas craftsmen and machine operators are tilted towards industry-specific skills.

In Appendix Section A.1, we validate our novel measure of training content generality using other variables from our data. The results evidence that our measures capture the general component of workers' skills.

3.5 Relevant Competition Measures

In the previous paragraphs we defined a new measure of training content generality. In this subsection, we define the appropriate measure of local labor market competition, in light of the mechanism highlighted in our theoretical model. To do so, the first necessary step is to clarify what should be the boundaries of local labor markets. We define local labor markets using the ISTAT definition of *Labour Market Areas*,[12] based on workers' commuting patterns. In total, the Italian territory is divided into 610 geographical units, defined using the commuting flows of Italian workers. In our data, we observe 590 units, as some locations did not participate in the policy we study. The main assumption we will make throughout the rest of the analysis is that workers are mobile *within* local labor markets, but not *across* them. This assumption allows us to elaborate a labor market competition measure at the local unit level, and exploit cross-sectional variation across local units to identify the effect

[12]Full documentation on the development of this classification can be found at: https://www.istat.it/en/labour-market-areas

	General Intensity		$\mathbb{I}$(General)		
	mean	median	mean	median	N
Panel A: Gender					
Male	0.48	0.40	0.58	1	155,746
Female	0.59	0.8	0.7	1	92,608
Panel B: Age					
<30	0.45	0.33	0.55	1	28,912
30-45	0.51	0.5	0.62	1	108,729
45-57	0.55	0.66	0.65	1	88,362
>57	0.57	0.8	0.66	1	22,351
Panel C: Hierarchy					
Apprentice	0.49	0.5	0.58	1	9,673
Prod. worker	0.39	0	0.47	0	98,510
Clerk	0.60	0.81	0.73	1	115,704
Middle manager	0.8	1	0.88	1	16,465
Upper manager	0.85	1	0.92	1	2,687
Panel D: Occupation					
Executives and clerks	0.69	1	0.8	1	42,300
Qualified service workers	0.37	0	0.48	0	37,733
Technicians	0.61	1	0.71	1	27,816
Unqualified workers	0.41	0	0.5	0	24,267
Craftsmen	0.39	0	0.47	0	26,309
Intellectual professions	0.65	1	0.73	1	14,944
Drivers and machine operators	0.33	0	0.44	0	14,381
Top managers and entrepreneurs	0.60	0.82	0.7	1	2,000

Table 4: Mean, median and count of the outcome variables across workers' types

of higher competition on firms' training decisions.

In the theoretical model, the crucial parameters that determine how much firms will invest in general versus industry-specific skills are the number of firms operating in the same

industry and the number of firms in other industries. We want to construct an empirical counterpart of these parameters, focusing on the group of establishments that are located in a given labor market, and that compete for the same pool of workers. Consider worker i, employed at firm j, located in local labor market $m(i)$ and in industry $k(j)$. We construct two different competition measures:

1. **External Competition** $N_{-k(j),m(i)}$: the number of establishments located in market $m(i)$ and in all industries different from $k(j)$

2. **Internal Competition** $N_{k(j),m(i)}$: the number of establishments located in market $m(i)$ and in industry $k(j)$

These measures vary at the *Industry* $\times$ *Local Labor Market* level, meaning that all the workers located in the same local labor market, employed at any establishment in the same industry, will be exposed to the same amount of External and Internal Competition. Moreover, we can aggregate the two measures into a single statistic and compute:

3. **Share of External Competitors:**

$$Sh_{k(j),m(i)} = \frac{N_{-k(j),m(i)}}{N_{-k(j),m(i)} + N_{k(j),m(i)}}$$

We use data from the ASIA-ULP register to calculate the number of establishments in each industry-market.[13] Throughout the rest of the empirical analysis we will use the natural logarithm of competition measures 1, and 2, and competition measure 3 as our main independent variables. Table 5 reports descriptive statistics for the three variables, collapsed at the *Industry* $\times$ *Local Labor Market* level.

[13] https://www.istat.it/it/censimenti/imprese

	$log\ N_{-k(j),m(i)}$	$log\ N_{k(j),m(i)}$	$Sh_{k(j),m(i)}$
Mean	9.18	5.39	.940
Min	5.79	0	.378
p25	8.54	4.15	.920
Median	9.08	5.36	.977
p75	9.67	6.60	.992
Max	12.92	11.53	.999
N	4,247	4,247	4,247

Table 5: key moments of the distribution of the 3 competition measures

3.6 Empirical Strategy

We exploit cross-sectional variation in the log-number of external competitors that establishments face to identify the effect of increased external competition on a firm's training type choice, while controlling for several variables that could correlate with both generality and competition measures. To identify the relevant comparisons, we include as controls a set of employees' characteristics, firm balance-sheet observables, as well as industry and local labor market fixed effects. The estimating equation is given by:

$$Y_{ij} = \alpha_0 + \alpha_1 Comp_{k(j),m(i)} + \Lambda_j'\xi + X_i\rho + \gamma_{h(i)} + \gamma_{k(j)} + \gamma_{m(i)} + \epsilon_{ij} \tag{6}$$

where Y_{ij} is our chosen training content generality measure (either $Gen.Intensity$ or $\mathbb{I}(General)$), for worker i, employed at firm j in local labor market m and industry k. We regress Y_{ij} on: a constant α_0; our chosen competition measure $Comp_{k(j),m(i)}$; Λ_j, a vector of firm controls that includes the log of total capital, value-added and total wage bill expenditures, the total amount of hours devoted to training and the share of the workforce trained; a vector X_i of worker controls, including gender, age, the number of training hours attended and the number of employers in the past 5 years. We also include a set of fixed effects, to partial-out the constant effect of a worker's hierarchical position γ_h, industry γ_k, and local labor market

γ_m. Since we only exploit cross-sectional variation, and the policy application period took place in the year 2021, we compute all time-varying measures in this year. The coefficient of interest is α_1, which can be interpreted as the effect of raising establishment j's number of external competitors on the share of general training received by worker i.

The main concern with equation (6) is that some unobserved workers' or establishments' characteristics might simultaneously drive the selection of workers into some training type and be correlated with the chosen competition measure. We address this concern in two ways: first, we increase the number of observables we control for by restricting the analysis to the group of workers that are matched to *Comunicazioni Obbligatorie*. For this group, we replace the hierarchy FE with more granular hierarchy $\times$ occupation FE, as shown in equation (7).

$$Y_{ij} = \alpha_0 + \alpha_1 Comp_{k(j),m(i)} + \Lambda_j'\xi + X_i\rho + \gamma_{o(i)h(i)} + \gamma_{k(j)} + \gamma_{m(i)} + \epsilon_{ij} \tag{7}$$

Second, we address the concern that firms with different training policies might sort into different labor markets by restricting the analysis to the sample of 2,029 multi-establishment firms. These are firms whose workers are located in more than a single local labor market: for this sample, we can compare workers that are employed at the same firm, hence with exactly the same production technology and training cost, but who are located in labor markets that differ in terms of the external competition they face. In practice, we do this by adding a firm fixed effect to specification (7), and removing the other firm-specific controls.

$$Y_{ij} = \beta_0 + \beta_1 Comp_{k(j),m(i)} + \delta_j + X_i\rho + \gamma_{h(i)} + \gamma_{k(j)} + \gamma_{m(i)} + \epsilon_{ij} \tag{8}$$

To attenuate potential bias coming from selection of workers into specific firms, we also include fixed effects at the firm $\times$ hierarchy level, as in equation (9), and at the firm $\times$ hierarchy $\times$ occupation level, as in equation (10).

$$Y_{ij} = \beta_0 + \beta_1 Comp_{k(j),m(i)} + \delta_j + X_i\rho + \gamma_{j,h(i)} + \gamma_{k(j)} + \gamma_{m(i)} + \epsilon_{ij} \tag{9}$$

$$Y_{ij} = \beta_0 + \beta_1 Comp_{k(j),m(i)} + \delta_j + X_i\rho + \gamma_{j,h(i),o(i)} + \gamma_{k(j)} + \gamma_{m(i)} + \epsilon_{ij} \tag{10}$$

For specifications (8), (9) and (10) the coefficient of interest is β_1, that can be interpreted as the effect of increasing external competition by one unit on worker i's share of general training, conditionally on i's employer firm j. If β_1 is negative and significantly different from 0, this means that firms are strategic when choosing the type of training that they provide to their workers: in particular, a negative β_1 would be consistent with our theoretical model. In fact, it implies that firms only prefer general over industry-specific training when external competition is low enough and the benefits from general training are larger than its *hold-up* cost.

3.7 Results

Tables 6 and 7 show the estimation results for the coefficient α_1 in equations (6) and (7), using as dependent variables the $General\ Intensity$ and $\mathbb{I}(General)$, respectively.

The empirical estimates confirm that firms exposed to a higher number of competitors in industries different than their own, provide their workers with a lower share of general training. Focusing on Table 6, all the coefficient estimates are negative and significantly different from zero, and they are robust to the use of worker hierarchy FE, as well as hierarchy $\times$ occupation FE. In columns 1 and 2 we assess the effect of increasing external competition on the dependent variable, holding constant the number of competitors from within the same industry, while in columns 3 and 4 the dependent variable of interest is the share of external competitors that a firm faces. The magnitude of the estimates is relevant across all the different specifications. For example, as implied by the coefficient from the third column

in Table 6, one standard deviation increase in the share of external competitors (which is approximately 0.095) lowers workers' general intensity score by 4.9 percentage points on average. Considering that the mean of the dependent variable is 0.488, this maps into a $\approx$ 10% reduction of the general intensity, for observations around the mean.

	(1)	(2)	(3)	(4)
DEP.VAR.	Gen.Intensity	Gen.Intensity	Gen.Intensity	Gen.Intensity
External Competition	-0.342**	-0.329**		
	(0.162)	(0.134)		
Internal Competition	0.00730	0.0114		
	(0.0185)	(0.0171)		
Share of External			-0.518***	-0.529***
Competitors			(0.184)	(0.158)
Mean(Dep.Var.)	0.488	0.465	0.488	0.465
Firm controls	✓	✓	✓	✓
Worker controls	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Hierarchy × Occupation FE		✓		✓
Firm FE				
Market FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	188,443	144,719	188,443	144,719
R-squared	0.230	0.266	0.230	0.266

s.e. clustered at the local labor market × industry level

Table 6: estimation results, equations 6 and 7; the dependent variable is $GeneralIntensity$. Column (1) reports the estimates from the specification with hierarchy FEs only, using as the main regressor the External Competition measure, while controlling for Internal Competition; column (2) adds FEs at the hierarchy × occupation level. Columns (3) and (4) are analogous, but use the share of external competitors as the main regressor

We find similar estimates when we use $\mathbb{I}(General)$ as the dependent variable. Looking at Table 7, we can interpret the results as the average reduction in the probability that a worker receives *some* general training, caused by a unit increase in our external competition measures.

We now move to the discussion of the results for the sample of multi-establishment firms only, following the empirical model detailed in equations (8), (9) and (10). Columns 1, 2, and 3 in Table 8 report the coefficient estimates when the main independent variable is the log-

DEP.VAR.	(1) $\mathbb{I}(General)$	(2) $\mathbb{I}(General)$	(3) $\mathbb{I}(General)$	(4) $\mathbb{I}(General)$
External Competition	-0.462**	-0.438**		
	(0.198)	(0.193)		
Internal Competition	-0.00944	0.000873		
	(0.0207)	(0.0195)		
Share of External Competitors			-0.519**	-0.574***
			(0.229)	(0.218)
Mean(Dep.Var.)	0.594	0.571	0.594	0.571
Firm controls	✓	✓	✓	✓
Worker controls	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Hierarchy × Occupation FE		✓		✓
Firm FE				
Market FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	188,443	144,719	188,443	144,719
R-squared	0.255	0.267	0.255	0.267

s.e. clustered at the local labor market x industry level

Table 7: estimation results, equations 6 and 7; the dependent variable is $\mathbb{I}(General)$. Column (1) applies firm and worker controls, location and industry FEs, as well as hierarchy FEs, using External Competition as the main regressor while controlling for Internal Competition. Column (2) replicates the same exercise, using FEs at the hierarchy × occupation level. Columns (3) and (4) are analogous, using the share of external competitors as the main dependent variable.

number of external competitors, controlling for the log-number of internal competitors and including firm and hierarchy FE, firm × hierarchy FE and firm × hierarchy × occupation FE, respectively. Columns 4, 5, and 6 use the local labor market share of external competitors as an independent variable. The coefficient estimates are always negative and significant at the 5% level, thus confirming the findings of the less restrictive regressions. In the most restrictive specification, we find that increasing by one standard deviation (1 percentage point) the share of local establishments in other industries lowers training content generality by approximately 5% with respect to the mean. Table 9 shows the results for the ME sample when the dependent variable is $\mathbb{I}(General)$. The results show that increasing by one standard deviation the share of local establishments in other industries lowers the probability that a worker receives some general training by approximately 6% with respect to the mean, in the

DEP.VAR.	(1) Gen.Int.	(2) Gen.Int.	(3) Gen.Int.	(4) Gen.Int.	(5) Gen.Int.	(6) Gen.Int.
External Competition	-0.356*	-0.544***	-0.267***			
	(0.186)	(0.173)	(0.0932)			
Internal Competition	-0.00869	-0.0144	-0.0167*			
	(0.0119)	(0.00986)	(0.00914)			
Share of External Competitors				-0.425*	-0.645***	-0.262**
				(0.230)	(0.222)	(0.107)
Mean(Dep.Var.)	0.502	0.502	0.470	0.502	0.502	0.470
Firm controls						
Worker controls	✓	✓	✓	✓	✓	✓
Hierarchy FE	✓			✓		
Firm FE	✓			✓		
Firm × Hierarchy FE		✓			✓	
Firm × Hierarchy FE × Occupation FE			✓			✓
Market FE	✓	✓	✓	✓	✓	✓
Industry FE						
Observations	128,349	127,817	90,700	128,349	127,817	90,700
R-squared	0.752	0.793	0.845	0.752	0.793	0.845

s.e. clustered at the local market × industry level

Table 8: estimation results, equations (8), (9) and (10); the dependent variable is *GeneralIntensity*. Columns (1), (2) and (3) use as main regressor the External Competition measure, while controlling for Internal Competition. They all include firm and worker controls and market FEs, and add respectively firm and hierarchy FEs, firm × hierarchy FEs and firm × hierarchy × occupation FEs. Columns (4), (5) and (6) do the same, but use the share of external competitors as their main regressor.

most restrictive specification.

One interesting result is that, across all the specifications, when we regress the generality measure on both the number of external competitors and the number of internal competitors, the coefficient associated to the number of internal competitors is hardly statistically significant, negative and of smaller magnitude. This suggests that the number of firms in the same industry does not affect training content choices. This finding allows us to rule out the potential role played by industrial districts: if firms were to benefit from knowledge externalities, due to the existence industrial districts, we would expect the coefficient associated to the number of internal competitors to be positive, as firms who can learn industry-specific skills from their peers would shift their investments to general training.

DEP.VAR.	(1) $\mathbb{I}(General)$	(2) $\mathbb{I}(General)$	(3) $\mathbb{I}(General)$	(4) $\mathbb{I}(General)$	(5) $\mathbb{I}(General)$	(6) $\mathbb{I}(General)$
External Competition	-0.535**	-0.720***	-0.350***			
	(0.246)	(0.235)	(0.134)			
Internal Competition	-0.0151	-0.0200*	-0.0218**			
	(0.0132)	(0.0114)	(0.0104)			
Share of External Competitors				-0.619**	-0.839***	-0.343**
				(0.299)	(0.295)	(0.151)
Mean(Dep.Var.)	0.609	0.609	0.579	0.609	0.609	0.579
Firm controls						
Worker controls	✓	✓	✓	✓	✓	✓
Hierarchy FE	✓			✓		
Firm FE	✓			✓		
Firm × Hierarchy FE		✓			✓	
Firm × Hierarchy FE × Occupation FE			✓			✓
Market FE	✓	✓	✓	✓	✓	✓
Industry FE						
Observations	128,349	127,817	90,700	128,349	127,817	90,700
R-squared	0.742	0.778	0.830	0.742	0.778	0.829

s.e. clustered at the labor market × industry level

Table 9: estimation results, equations (8), (9) and (10); the dependent variable is $\mathbb{I}(General)$. Columns (1), (2) and (3) use as main regressor the External Competition measure, while controlling for Internal Competition. They all include firm and worker controls and market FEs, and add respectively firm and hierarchy FEs, firm × hierarchy FEs and firm × hierarchy × occupation FEs. Columns (4), (5) and (6) are analogous, but use the share of external competitors as their main regressor.

Overall, the findings are consistent with the mechanism proposed by the theoretical model in Section 3. The fact that both the analysis in the full sample and in the sample of multi-establishment firms, under a variety of empirical specifications, show similar results confirms our initial hypothesis that firms act strategically and provide their workers with more industry-specific skills when the risk that the workers will be poached is higher. Figure 1 provides a graphical summary of our coefficient estimates, under different samples and model specifications.

Brunello and Gambarotto 2007 identify agglomeration economies as another potential determinant of firms' training intensity. Indeed, the existence of agglomeration economies increases the returns from complementarity between skilled workers and increases the in-

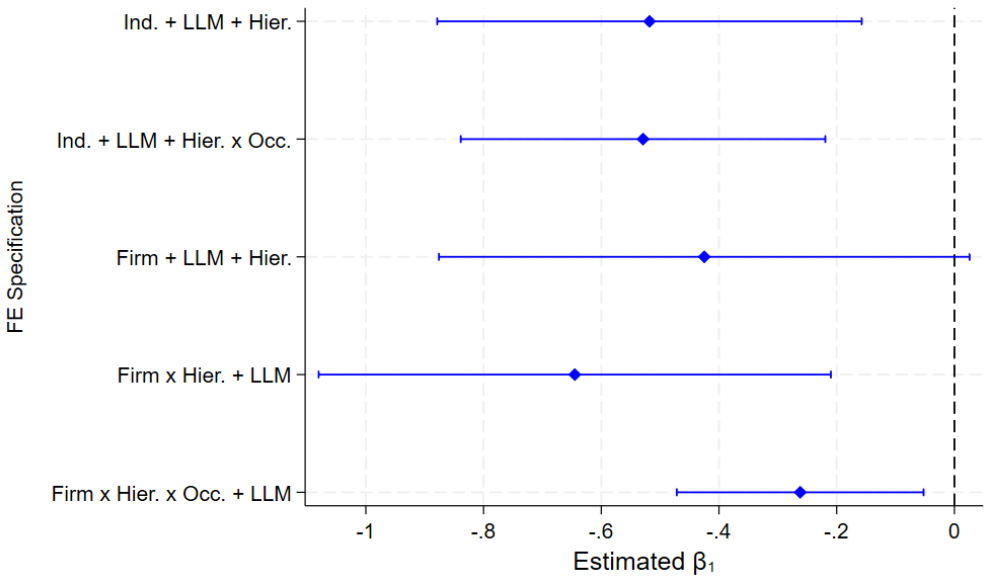


Figure 1: Coefficient estimates for $\hat{\beta}_1$, for different combinations of fixed effects. S.E. are clustered at the industry $\times$ local market level. The dependent variable is General Intensity, and the main regressor is the share of external competitors.

centives for firms to train. Therefore, if there was any effect of agglomeration economies, not captured by the location fixed effects, it would push our estimates toward zero. In that case, we could consider our coefficients as a lower bound of the true effect of competition on training type choice.

We analyze heterogeneity of our results with respect to one important dimension: workers' skill level. Our expectation is that high-skill workers should have a larger outside option and be more mobile. Firms should be particularly concerned about providing general skills to these workers, especially in competitive markets. Since we do not have a direct measure of skill, we interact our baseline coefficient with broad occupational classifications. Figure 2 displays the estimated interaction coefficients. As shown in the figure, the effect appears to be concentrated among white collar workers. We believe this could be explained by two forces: first, white collars are those that might need general skills more than blue collars; second, white collars are likely to be more educated and potentially more mobile. This would suggest that firms provide specific skills in a strategic way, focusing on those workers that are more likely to be poached by competitors in the labor market.

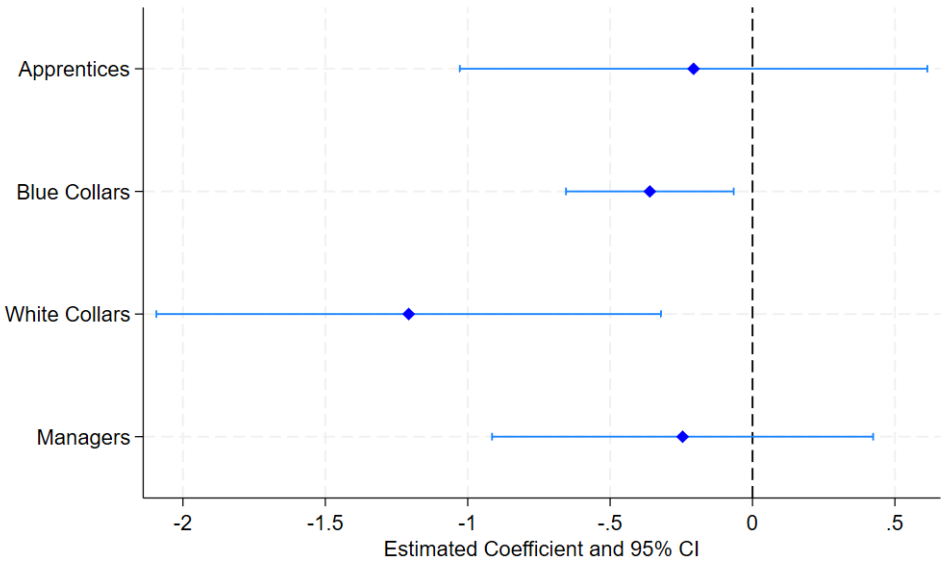


Figure 2: Coefficient estimates for $\hat{\beta}_1$, interacting the competition measure with 1-Digit Occupational Codes. FEs are included at the Firm + LLM + Hierarchy level.

We perform two important robustness checks on the way training content generality is measured: first, we remove from the sample of training courses soft skills and languages, since, as explained in Section 2, firms were not obliged to report in their application packages the ADA codes for these activities. Hence, in the main analysis, we interpret missing codes as characterizing general skills. In the Appendix, we repeat the whole analysis without this assumption. As shown in Appendix Section A.4, this does not change our main results. Secondly, we repeat the analysis after dropping from the sample all the cases in which the ADA code filed for a course does not match with those related to general skills, nor to the industry to which the trained worker belongs. Even in this case, our results do not change significantly.

Moreover, in Tables A7 and A8 we check what happens if we replace our competition measure based on the number of firms, with a new measure that weights each firm by its employment. Even in this case, the results are qualitatively unchanged, and estimates remain statistically significant in most of the specifications.

4 Quasi-Experimental Analysis on Fondimpresa Data

Despite the extensive set of granular worker- and firm-level controls we employ, concerns may remain regarding identification and the external validity of our results beyond the FNC firms. To mitigate this concern, we collect establishment-year level data for firms funded by the largest inter-professional fund: *Fondimpresa*. Access to this dataset also allows us to exploit the time dimension to estimate exogenous variation in local labor market competition using a Bartik instrument.

Inter-professional funds are the primary mechanism through which Italian firms finance training projects. Established in 2000, they are jointly managed by representatives of employers' and workers' associations. These funds are financed by a government-mandated payroll tax of approximately 0.30% of each worker's annual salary. Their exclusive purpose is to redistribute resources to firms to support employee training.

Fondimpresa is the largest of these funds, covering approximately 210,000 firms and 4.9 million workers. It distributes resources primarily through two channels: the *Conto Formazione*, which allows firms to recover contributions on an individual basis, and competitive calls for proposals, through which firms apply for grants under specified conditions.

4.1 Data and Descriptive Statistics

Firms

We use establishment-level data on all training projects financed through the *Conto Formazione* channel from 2011 to 2023, excluding mandatory workplace safety training projects. The panel nature of this dataset enables us to construct a Bartik-like instrument for our dependent variable and to implement dynamic versions of specifications (8) and (9) from Section 3.

Since we are interested in firms' autonomous training choices in response to local labor market conditions, we restrict our sample to projects financed via *Conto Formazione*, excluding topic-based grants with externally imposed training content. This choice limits our analysis to larger firms compared to the FNC sample. As shown in Table 10, *Fondimpresa* firms are significantly larger than both FNC participants and the average Italian firm. Figure 16 confirms this by comparing distributions of sales across samples.

	ln Sales	ln V. Added	ln Employees	ln Labor Cost	ln Capital	ln Profits
Fondimpresa Sample:						
Mean	9.885	8.745	4.407	8.307	8.529	6.575
Std. Dev.	1.709	1.561	1.317	1.539	2.471	2.103
FNC Sample:						
Mean	7.966	6.905	3.130	6.524	6.058	4.433
Std. Dev.	1.709	1.561	1.317	1.539	2.471	2.103
All Firms:						
Mean	5.724	4.553	1.630	4.282	4.195	3.002
Std. Dev.	2.012	1.969	1.198	2.260	2.685	2.043
Difference with FNC	2.004***	1.925***	1.342***	1.866***	2.580***	2.226***
	(0.034)	(0.031)	(0.026)	(0.030)	(0.048)	(0.046)
Difference with IT	4.159***	4.189***	2.775***	4.021***	4.336***	3.575***
	(0.033)	(0.032)	(0.020)	(0.037)	(0.044)	(0.036)

Table 10: Summary statistics of key balance-sheet variables for *Fondimpresa* firms, FNC firms, and other Italian firms. Monetary variables are measured in millions of euros. Differences in means are estimated through regressions controlling for multiple sample memberships.

4.2 Measurement of Training Content Generality

To test our research hypotheses, we construct a measure of training content generality based on short textual descriptions of each training session, coupled with establishment-level worker participation counts. The measure is constructed as follows:

1 Construct a tf-idf vector of words $\mathbf{w}_{i,t}$ used in each establishment i in year t, where we weight each class by the number of workers attending it.

2 Measure the cosine similarity $\sigma_{ij,t}$ of each vector $\mathbf{w}_{i,t}$ to all other establishments' vectors $\mathbf{w}_{j,t}$, $\forall j \neq i$.

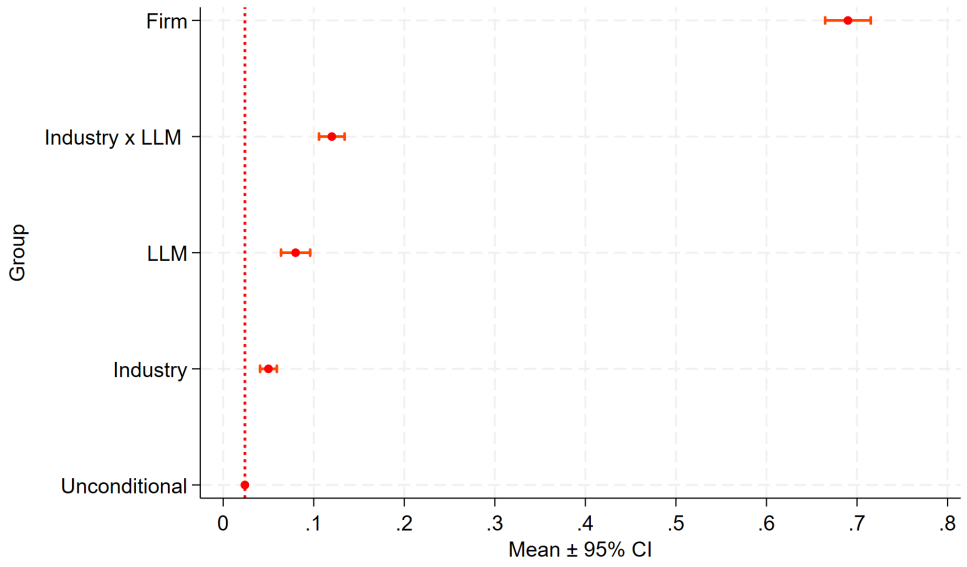


Figure 3: We calculate the average similarity score by averaging across firms within the same group (groups are indicated on the y axis).

3 For each establishment, average across all cosine similarities: $\overline{\sigma}_{i,t} = \frac{\sum_j \sigma_{ij,t}}{N-1}$.

The distribution of the average similarity score is plotted in Figure 17. Higher average cosine similarity indicates a relatively more general training content. Unlike FNC data, the *Fondimpresa* data set lacks ADA classification codes, preventing a distinction between fully general and industry-specific training types. Consequently, our poaching risk measure also differs, as described in the following. Table A9 summarizes the main variables at the establishment level used in the analysis.

To validate our measure, we compute average similarity scores within different groups, defined by parent company, local labor market, industry, and industry-local market pairs. Figure 3 shows that, as we increase the size of the group, the average similarity score drops: this supports the validity of the constructed generality measure.

4.3 Measurement of Poaching Risk

We measure establishments' exposure to poaching risk using the *Comunicazioni Obbligatorie* (COB) dataset, introduced in Section 2.1. This dataset allows us to track all voluntary worker transitions across establishments, aggregated by industry and local labor market, between 2015 and 2019. We restrict the analysis to **voluntary quits** in which employees move to a new employer within the same calendar year.

For each local market-industry pair (j, l) and year t we compute our **Poaching Risk Measure** as share of movers for each industry-llm pair in a year:

$$PR_{j,l,t} = \frac{m_{j,l,t}}{N_{j,l,t}}$$

where:

- $m_{j,l,t}$ is the total number of movers from industry j, local labor market l and year t;
- $N_{j,l,t}$ is the total number of employees in each (j, l, t).

Figure 4 illustrates the distribution of the poaching risk measure across markets and industries.

4.4 Empirical Analysis

To evaluate the effect of poaching risk on training generality, we estimate the following specification for establishment i in local market $l(i)$, industry $j(i)$, and year t:

$$\overline{\sigma}_{i,j,l,t} = \beta_0 + \beta_1 PoachingRisk_{j,l,t-1} + \underbrace{\gamma_{j,t}}_{\text{industry-year FE}} + \underbrace{\gamma_{l,t}}_{\text{llm-year FE}} + \epsilon_{i,j,l,t} \tag{11}$$

where $\overline{\sigma}_{i,j,l,t}$ denotes the generality score of training content and $\text{PoachingRisk}_{j,l,t-1}$ is lagged by one year. We control for local market, industry, firm, and time fixed effects. The coef-

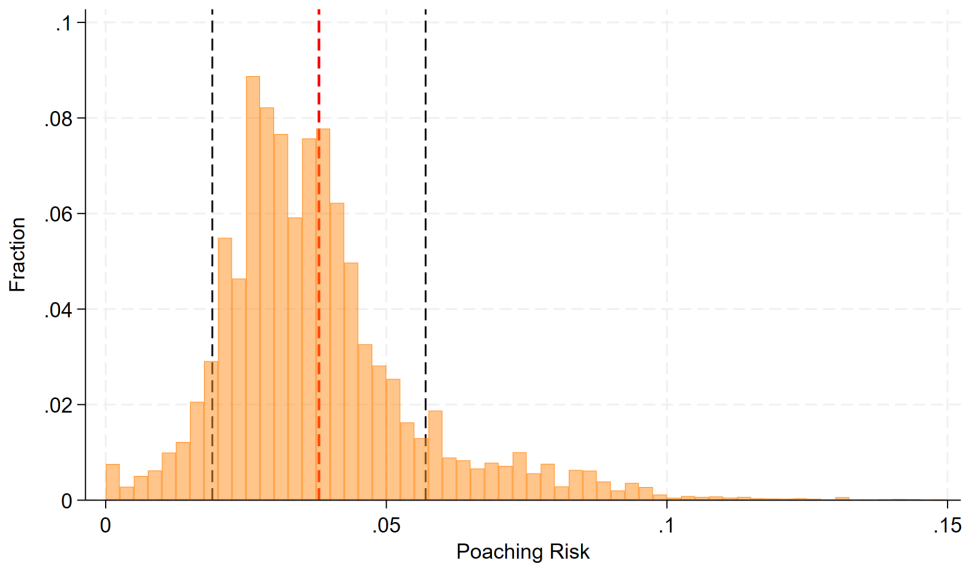


Figure 4: Empirical Distribution of the poaching risk variable. The red vertical line corresponds to the mean level, while the dark vertical lines indicate 1 s.d. differences from the mean.

ficient β_1 measures how an increase in poaching risk affects the average generality score of firms in a given local market and industry. However, two potential threats could compromise identification of this effect. First, despite including industry-year and local market-year fixed effects, poaching risk may remain correlated with the error term due to omitted variable bias. For instance, industry-local market specific productivity shocks could *simultaneously* affect both training choices and poaching risk. We address this concern by implementing an instrumental variable strategy, discussed in the next paragraph. Second, sample selection bias could arise if firms select into the *Fondimpresa* sample based on poaching risk, potentially biasing our estimate of β_1. In the following paragraph, we also demonstrate that poaching risk does not drive firms' selection into training programs, thereby mitigating sample selection concerns.

4.4.1 Instrumental Variable Strategy

To address potential omitted variable bias, we isolate plausibly exogenous variation in poaching risk by exploiting pre-existing co-worker networks and time-varying labor demand shocks,

following the approaches of Caldwell and Harmon 2019 and Sorkin 2018. We define a market as the combination of an industry and local labor market pair: $m = (j \times l)$. Specifically, we construct an instrument for the poaching risk measure by implementing the following steps:

1. We compute $S_{m,n,2015}$: the 2015 shares of total employment in market m that moved to market $n \neq m$.

2. We obtain labor demand shocks in external markets, $Shift_{n,t}$, computed as $Empl_{n,t} - Empl_{n,t-1}$. We obtain the time-series employment data for each market from the ISTAT database.

3. We construct the instrument as $IV_{m,t} = \sum_{n \neq m} S_{m,n,2015} \times Shift_{n,t}$.

Figure 5 provides a graphical explanation of these steps. The instrument predicts the number of employees leaving market m at time t, given the 2015 mobility patterns and local employment demand shocks.

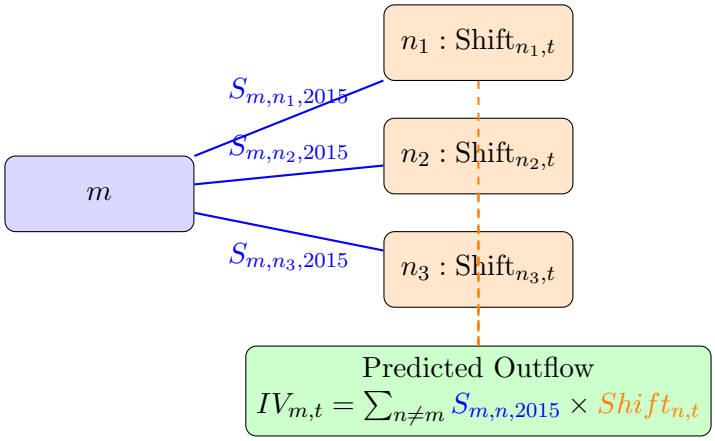


Figure 5: Network-flows based IV

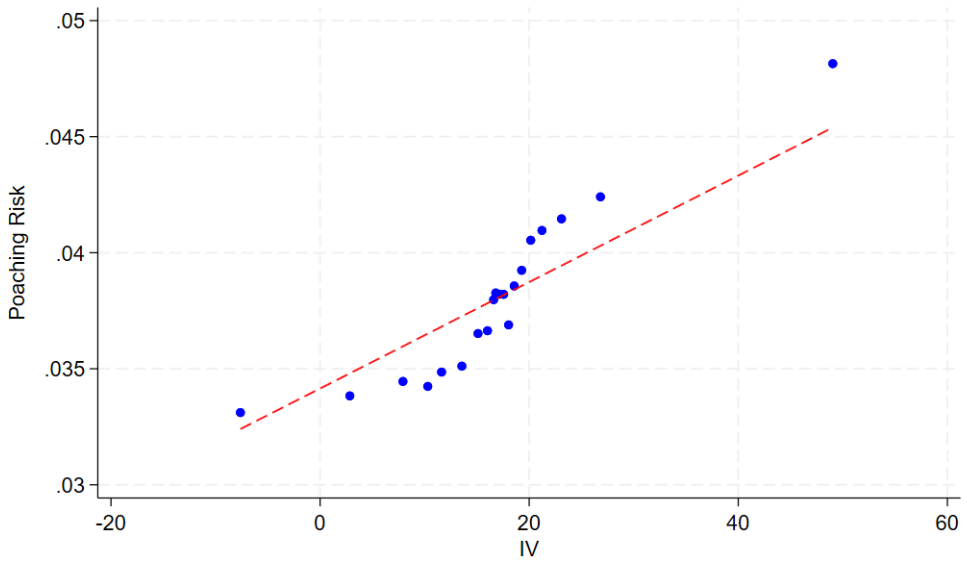
The instrument we construct is *Bartik-like*, as it relies on a **weighted sum** of **shocks**, where the **weights** reflect an **exposure** structure. Recent literature has shown that identification must rely on either the exogeneity of the shifts (Borusyak et al. 2022) or the exogeneity of the shares (Goldsmith-Pinkham et al. 2020). In our context, the first assumption is not

credible: shocks could be correlated across locations (for example, technology shocks that affect multiple locations simultaneously). Our instrument-based identification therefore relies on the exogeneity of the 2015 shares. We believe this assumption is plausible, as the 2015 shares likely reflect pre-determined mobility patterns that do not correlate with time-varying training decisions. We provide additional evidence supporting this assumption in Appendix Section A.5. Table 11 reports the results from our IV strategy. Columns (1) and (3) report

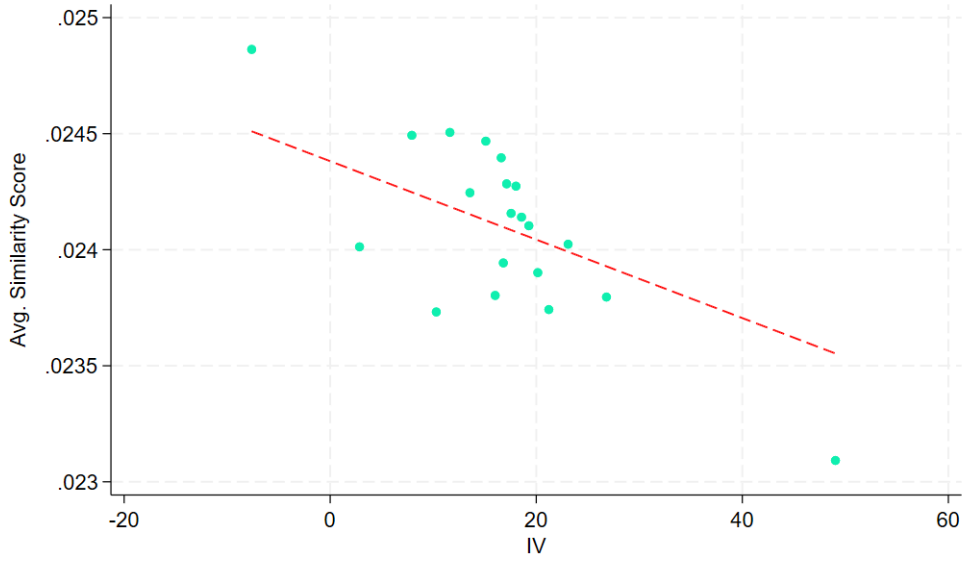
Dep. Var.: Training Content Generality				
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Estimates				
Poaching Risk$_{t-1}$	-0.012*	-0.074***	-0.006	-0.061*
	(0.006)	(0.029)	(0.006)	(0.032)
1st Stage F-stat		51.4		34.6
Fixed Effects				
$industry \times year$	✓	✓		
$llm \times year$	✓	✓	✓	✓
$firm \times year$			✓	✓
Observations	31,262	31,255	11,420	11,417
s.e. clustered at the $indsustry \times llm$				

Table 11: Results from estimating specification 11. The mean of the dependent variable is 0.024. 1 s.d. in Poaching Risk corresponds to 0.02.

the results from estimating equation 11 with simple OLS, under different FE specifications. Columns (2) and (4) report the corresponding 2SLS estimates. The instrument we use is relevant, with 1st Stage F-Stats well above 10: Figure 6 represents graphically the first stage regression and the reduced form for our 2SLS estimation: for both regressions, we residualize the dependent variable on the set of FEs, and then plot its average for vingtiles of the IV. As shown in Table 11, the estimated coefficient of interest is always negative, consistently with our theoretical model and confirming the previous finding. The IV estimates are larger and always statistically different from zero. Moreover, as shown in the last column, they are robust to the inclusion of $firm \times year$ FEs. In terms of the magnitude, the results are comparable to the ones obtained in Section 3: taking the coefficient estimate in column (2)



1st Stage Regression



Reduced Form

Figure 6: Graphical representation of the first stage regression and the reduced form for the 2SLS estimation. For both regressions, the dependent variable is residualized on the set of fixed effects and plotted as averages over vingtiles of the instrument.

as a baseline, a 1 s.d. increase in our measure of Poaching Risk is associated with $\approx 6\%$ decrease in training generality, relative to the mean.

Standard errors are clustered at the $industry \times llm$ level. In Figure 18 we report robustness

tests of the estimated coefficient to alternative cluster choices.

4.4.2 Addressing Sample Selection Concerns

Sample Selection might introduce a bias in our estimate of coefficient β_1 from equation 11, as long as selection into our sample is correlated with our independent variable of interest, Poaching Risk. To show that this does not happen, we aggregate the share of firms in each $industry \times llm \times year$ that join Fondimpresa: to do so, we divide the total number of firms in our dataset over the total number of firms, in the same unit, available on the ISTAT website. Using this measure of participation rate, we show empirically that it does not correlate with Poaching Risk. In particular, we estimate the following model:

$$Sh.Fondimpresa_{j,l,t} = \alpha_0 + \alpha_1 PoachingRisk_{j,l,t} + \underbrace{\gamma_{l,t}}_{\text{market} \times \text{time FEs}} + \underbrace{\gamma_{j,t}}_{\text{industry} \times \text{time FEs}} + \epsilon_{j,l,t} \tag{12}$$

We report the coefficient estimates for coefficient α_1 in equation in Figure 7, for different specifications of the regression model. As shown in the figure, the estimated coefficient is always small and never significant at the 95% level. As soon as we include market $\times$ industry FEs among the controls, the coefficient is not even signficant at the 90% level. Overall, this suggests that the Poaching Risk does not drive selection of firms into our sample, thus mitigating sample selection concerns.

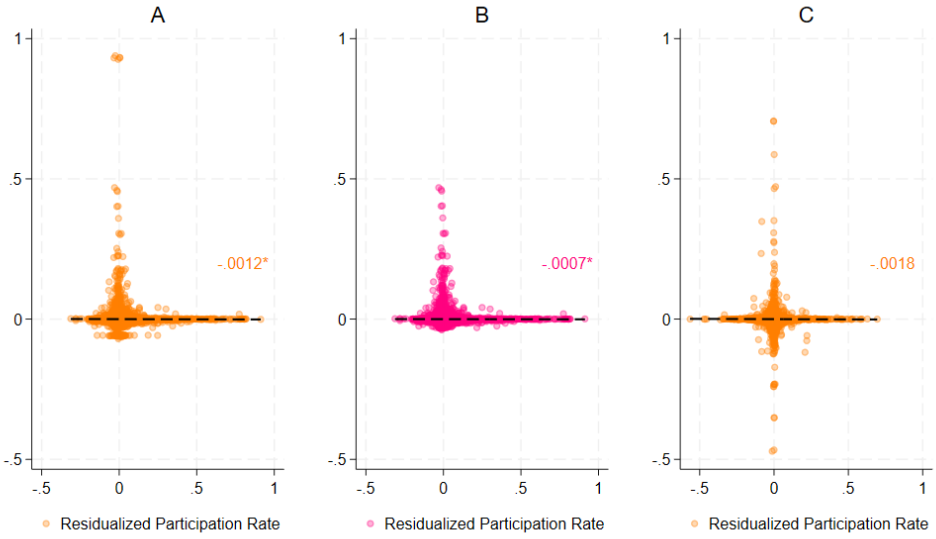


Figure 7: Panel A plots the correlation of the Fondimpresa Share with poaching risk after residualizing both variables on controls; Panel B also does the same, after dropping outliers of the Fondimpresa Share; Panel C includes $industry \times llm$ FEs among the controls.

5 Conclusions

Using novel data from a large-scale policy that provided grants to Italian firms for worker training in 2021, we find that firms facing greater labor market competition tend to invest more in specific training for their workers. To explain this, we develop a theoretical model of firms' training investment that incorporates labor market competition and workers' heterogeneous preferences. Our empirical analysis leverages both cross-firm comparisons, examining workers employed at firms with different characteristics, and within-firm comparisons, focusing on workers at the same firms but located in different local labor markets.

To deal with potential issues of endogeneity of our competition measures and of external validity, we extend our using a different dataset with a repeated cross-section of firm-provided training. We use this dataset to construct a shift-share instrument and identify exogenous variations in the poaching risk that firms face. The estimates confirm the results from the first part of analysis.

We view these results as an important first step towards understanding how labor market competition influences firms' internal human capital investments. Recent evidence (Jedwab et al. 2023; Ma et al. 2024) highlights human capital accumulation as a critical driver of economic development. This paper adds to that discussion by showing how the success of labor market policies is closely tied to the characteristics of local labor markets. One potential improvement suggested by our analysis is to complement governmental training subsidies with restrictions on the *type* of training to be provided. Such restrictions could be conditional on the degree of labor market competition faced by the subsidized firms, ensuring that firms in more competitive labor markets need to include some general training among the courses offered to employees. Further research into the interaction between local economic conditions and firms' decision-making processes not only presents a valuable research opportunity but also represents a crucial step toward designing more effective policy interventions.

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A Appendix

A.1 Measurement Validation

In order to validate our newly-developed measure of training content generality, we exploit the match to *Comunicazioni Obbligatorie* to leverage information on workers' E to E transitions. Doing so, we perform two separate exercises: first, we look at *voluntary* leaves, and try to predict the likelihood that a worker leaves its original firm for a new employer, using our generality measures. If our measures are correct, we should expect that workers exposed to general training will leave their original firm with higher probability: most importantly, we should expect these workers to move more easily across industrial sectors.
To alleviate possible concerns about the *endogeneity* of the leaving decision, we will repeat the same exercise for the sample of *involuntary* leavers. In particular, we will exploit identification coming from mass lay-offs, since in these cases firing decisions are likely uncorrelated to firms' training-content choices. In our data, we define a mass layoff as an event where more than 30% of the workforce is fired at the same time, for firms with less than 50 employees. For larger employers, we look at those who simultaneously fire more than 10% of their workforce.

Figure 15 plots the total number of transitions for workers that received some general training and for those who didn't. Not only the first group displays a larger number of leaves, but also a larger share of transitions to sectors different from the one of origin.
Just comparing the number of transitions is not enough to claim that workers exposed to general training are more likely to move to other sectors. In order to control for possible correlated observables, given a worker i employed by firm j, we regress our outcomes of interest Y_{ijm} on the chosen generality measures, fixed effects at the location $m(i)$, industry $k(j)$, worker hierarchy $h(i)$ and occupation $o(i)$ level, a vector of controls at the firm level Λ_j, including firm balance sheet observables (valueadded, salaries, total capital) and training

information (total training hours, firm's share of trained workers), and worker controls X_i, including demographics (gender and age) and the number of transitions realized by worker i in the past 5 years:

$$Y_{ijm} = \alpha_0 + \beta_1 Gen_{ijm} + \delta_k + \delta_m + \delta_h + \delta_o + \Lambda_i'\xi + X_j'\rho + \epsilon_{ijm} \tag{13}$$

First, we run equation 13 to predict the likelihood of voluntary transition overall, and across different industries. Estimation results are reported in Table A1. While no significant effect is found in terms of voluntary transition probability, it seems that, conditional on leaving, workers who received general training have a greater chance to move to an employer in a different sector.

	(1)	(2)	(3)	(4)
DEP.VAR	$\mathbb{P}$(leave)	$\mathbb{P}$(leave)	$\mathbb{P}$(diff.sector | leave)	$\mathbb{P}$(diff.sector | leave)
Gen.Intensity	-0.0007		0.020**	
	(0.002)		(0.009)	
$\mathbb{I}$(General)		-0.0002		0.026***
		(0.002)		(0.008)
Firm-level controls	✓	✓	✓	✓
Worker-level controls	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Location FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	144,732	144,732	17,919	17,919
R-squared	0.06	0.06	0.129	0.129

Table A1: estimation results for the probability of voluntarily leaving the firm (columns 1 and 2) and for the probability of moving to a different sector, conditional on a voluntary leave (columns 3 and 4)

The same exercise is repeated in the sub-sample of workers affected by mass-layoffs. As shown in Table A2, workers that receive general training are more likely to find a new job, compared to those who did not. The findings are not significant when analyzing movements

from one industry to the other.

VARIABLES	(1) $\mathbb{P}$(new job)	(2) $\mathbb{P}$(new job)	(3) $\mathbb{P}$(diff.sector | new job)	(4) $\mathbb{P}$(diff.sector | new job)
Gen.Intensity	0.295***		0.042	
	(0.042)		(0.048)	
$\mathbb{I}$(General)		0.227***		0.033
		(0.038)		(0.049)
Firm-level controls	✓	✓	✓	✓
Worker-level controls	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Location FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	2,297	2,297	1,253	1,253
R-squared	0.507	0.507	0.438	0.438

Table A2: Estimation results the probability of finding a new job (columns 1 and 2) and for the probability of moving to a different sector, conditional finding a new job (columns 3 and 4)

Notice that the sample numerosity is low when focusing on mass-layoffs, especially in the case of columns (3) and (4) of Table A2: despite this *caveat*, the results are still suggestive that our chosen measures capture the degree of generality of the training to which workers have been exposed. Armed with such measures, we will be able to answer our main research question in the next sections.

A.2 Derivation of Equation 4

We start from the definition of π_{ij}, given in equation (2):

$$\pi_{ij}(g, s; N_k, N_\rho) = \frac{exp[\gamma f(g,s)]}{N_k exp[\gamma f(g,s)] + N_\rho exp[\gamma f(g,0)]}$$

Compute the derivatives of π_{ij} with respect to g:

$$\frac{\partial \pi}{\partial g} = \frac{exp[\gamma f(g,s)]\gamma f_g}{N_k exp[\gamma f(g,s)] + N_\rho exp[\gamma f(g,0)]} - \frac{exp[\gamma f(g,s)]}{\{N_k exp[\gamma f(g,s)] + N_\rho exp[\gamma f(g,0)]\}^2}[N_k exp[\gamma f(g,s)]\gamma f_g + N_\rho exp[\gamma f(g,0)]\gamma f_g]$$

Define $N_k exp[\gamma f(g,s)] + N_\rho exp[\gamma f(g,0)] = M$

$$\frac{\partial \pi}{\partial g} = \frac{exp[\gamma f(g,s)]\gamma f_g}{M} - \frac{exp[\gamma f(g,s)]\gamma f_g}{M^2}[N_k exp[\gamma f(g,s)] + N_\rho exp[\gamma f(g,0)]] = 0$$

Similarly, compute the derivative of π_{ij} with respect to s:

$$\begin{aligned}\frac{\partial \pi}{\partial s} &= \frac{exp[\gamma f(g,s)]\gamma f_g}{M} - \frac{exp[\gamma f(g,s)]}{M^2}[N_k exp[\gamma f(g,s)]\gamma f_s] \\ &= \frac{exp[\gamma f(g,s)]\gamma f_g}{M}\gamma f_s \left[1 - \frac{N_k exp(\gamma f(g,s))}{M}\right] \\ &= \pi \gamma f_s \Omega\end{aligned}$$

Finally, plug the two derivatives into the first order conditions of the firm's problem:

$$[g] : \pi(1-\alpha) f_g = c_g$$

$$[s] : \pi \gamma f_s \Omega (1-\alpha) f(g,s) + \pi(1-\alpha) f_s = c_s$$

After dividing both equations by $\pi(1-\alpha)$, we get:

$$[g] : f_g = c_g/(\pi(1-\alpha))$$

$$[s] : (\gamma f(g,s)\Omega + 1) f_s = c_s/(\pi(1-\alpha))$$

Taking the ratio of the FOCs, we obtain equation (4).

A.3 Conditions for Existence of a Global Maximum to the Firm's Problem

In Section 3.3, we identify the system of first order conditions associated to the firm's profit maximization problem. In order for the FOCs to be both necessary and sufficient for the existence of a global solution, we need to verify that the objective function is concave, This corresponds to checking that the Hessian matrix of second order conditions is negative-definite. Assuming that the production function is linear and separable in the two inputs, and that the cost function is quadratic in each input and separable, the second order conditions are the following:

$$
\begin{aligned}
&[gg]: \ \pi_g(1-\alpha)a - 2\kappa_g = 0 \\
&[gs]: \ \pi_s(1-\alpha)a = 0 \\
&[sg]: \ \pi_s(1-\alpha)a = 0 \\
&[ss]: \ (1-\alpha)\left[\pi_{ss}(ag+bs)+\pi_s b\right] + \pi_s(1-\alpha)b - 2\kappa_s = 0
\end{aligned}
$$

where π_s and π_g are the derivative of $\pi(g,s)$ with respect to s and g, respectively, and π_{ss} is the second derivative of $\pi(g,s)$ with respect to s.

In section A.2, it has been shown that, thanks to the separability assumption, $\pi_g = 0$. The Hessian matrix can hence be written as:

$$
\begin{bmatrix}
-2\kappa_g & \pi_s(1-\alpha)a \\
\pi_s(1-\alpha)a & (1-\alpha)\left[\pi_{ss}(ag+bs)+2\pi_s b\right] - 2\kappa_s
\end{bmatrix} = H
$$

Remember now that $\pi_s = \pi\gamma f_s\Omega = \pi\gamma b\Omega \geq 0$. We can hence compute $\pi_{ss} = \frac{\partial\pi(g,s)}{\partial s\partial s}$:

$$\begin{aligned}\pi_{ss} &= \frac{\partial(\pi\gamma b\Omega)}{\partial s} = \gamma b\frac{\partial}{\partial s}(\pi\Omega) \\ &= \gamma b\left[\pi_s\Omega + \pi\frac{\partial\Omega}{\partial s}\right]\end{aligned}$$

We first compute

$$\begin{aligned}\frac{\partial\Omega}{\partial s} &= \frac{\partial}{\partial s}\left(\frac{N_\rho exp(\gamma ag)}{(N_\rho exp(\gamma ag) + N_k exp(\gamma(ag+bs))}\right) \\ &= \frac{N_\rho exp(\gamma ag)}{(N_\rho exp(\gamma ag) + N_k exp(\gamma(ag+bs))^2}(-1)N_k exp(\gamma(ag+bs))\gamma b \\ &= (-1)\gamma b\Omega(1-\Omega)\end{aligned}$$

So that

$$\begin{aligned}\pi_{ss} &= \gamma b\left[\pi_s\Omega + \pi\frac{\partial\Omega}{\partial s}\right] \\ &= \gamma\left[\pi\gamma b\Omega b\Omega + \pi b(-1)\gamma b\Omega(1-\Omega)\right] \\ &= \gamma\left[\pi\gamma b\Omega b\Omega + \pi\gamma b\Omega b\Omega - \pi b\gamma b\Omega\right] \\ &= \gamma\left[2\pi\gamma b^2\Omega^2 - \pi\gamma b^2\Omega\right] = \gamma\pi\gamma b^2\Omega(2\Omega-1)\end{aligned}$$

We can then re-write the Hessian matrix as:

$$\begin{aligned}H &= \begin{bmatrix} -2\kappa_g & \pi\gamma b\Omega(1-\alpha)a \\ \pi\gamma b\Omega(1-\alpha)a & (1-\alpha)\left[\gamma\pi\gamma\beta^2\Omega(2\Omega-1)\right](ag+bs) + 2\pi\gamma b^2\Omega] - 2\kappa_s \end{bmatrix} \\ &= \begin{bmatrix} -2\kappa_g & \pi\gamma b\Omega(1-\alpha)a \\ \pi\gamma b\Omega(1-\alpha)a & (1-\alpha)\pi\gamma b^2\Omega\left[(2\Omega-1)\gamma(ag+bs) + 2\right] - 2\kappa_s \end{bmatrix}\end{aligned}$$

In order for the problem to admit a global maximum, we want the matrix H to be negative-definite. Since the matrix is symmetric and 2x2, this happens if the first principal minor is

negative and the second principal minor (the determinant) is positive. The first is always true, since the first principal minor is is $-2\kappa_g$, with $\kappa_g > 0$. We only need to check what are the conditions under which the determinant is positive. That boils down to verifying the following inequality:

$$4\kappa_g\kappa_s - 2\kappa_g\left[(1-\alpha)\pi\gamma b^2\Omega\left[(2\Omega-1)\gamma(ag+bs)+2\right]\right] > \left((1-\alpha)\pi\gamma ab\Omega\right)^2$$

$$4\kappa_g\kappa_s > \left((1-\alpha)\pi\gamma ab\Omega\right)^2 + 2\kappa_g\left[(1-\alpha)\pi\gamma b^2\Omega\left[(2\Omega-1)\gamma(ag+bs)+2\right]\right]$$

Notice that all the parameters are greater or equal to zero. It is particularly easy to verify that the parameter κ_s is only present in the left-hand side of the inequality: hence, a large enough value of this parameter will be enough to make sure that a solution to the firm-maximization problem exists and is unique.

A.4 Section 3: Robustness Checks

Table A3 reports the estimation results for equations (6) and (7), when the training courses for which ADA = 0 are excluded from the computation of training content measures. Table A4 reports the same estimates for the sample of multi-establishment firms. Similarly, Tables A5 and A6 report the estimation results when we exclude from the computation of training content measures those training courses where the ADA code does not match either the firm's industry, nor the general training codes. Tables A7 and A8 report the results when our baseline models are estimated using the number of employees, instead of the number of firms, as our independent variable.

	(1)	(2)	(3)	(4)
Panel A				
DEP.VAR.	*Gen.Int.*	*Gen.Int.*	*Gen.Int.*	*Gen.Int.*
External Competition	-0.399***	-0.295**		
	(0.134)	(0.131)		
Internal Competition	-0.0104	0.00222		
	(0.0178)	(0.0168)		
Share of External Competitors			-0.458***	-0.419***
			(0.155)	(0.140)
Panel B				
DEP.VAR.	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$
External Competition	-0.570***	-0.449**		
	(0.186)	(0.187)		
Internal Competition	-0.0338	-0.0113		
	(0.0214)	(0.0202)		
Share of External Competitors			-0.479**	-0.505**
			(0.216)	(0.196)
Firm controls	✓	✓	✓	✓
Worker controls	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Hierarchy × Occupation FE		✓		✓
Firm FE				
Market FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	168,348	131,152	168,348	131,152

s.e. clustered at the local labor market × industry level

Table A3: estimation results, equations 6 and 7; the dependent variable is *General Intensity* in Panel A, $\mathbb{I}(General)$ in Panel B

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
DEP.VAR	*Gen.Int.*	*Gen.Int.*	*Gen.Int.*	*Gen.Int.*	*Gen.Int.*	*Gen.Int.*
External Competition	-0.362*	-0.578***	-0.276**			
	(0.199)	(0.183)	(0.108)			
Internal Competition	-0.000212	-0.0149	-0.0158			
	(0.0138)	(0.0114)	(0.0107)			
Share of External Competitors				-0.484**	-0.687***	-0.278**
				(0.229)	(0.224)	(0.115)
Panel B						
DEP.VAR	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$
External Competition	-0.628**	-0.850***	-0.401**			
	(0.282)	(0.269)	(0.161)			
Internal Competition	-0.0111	-0.0258*	-0.0222*			
	(0.0158)	(0.0134)	(0.0123)			
Share of External Competitors				-0.768**	-0.982***	-0.409**
				(0.326)	(0.323)	(0.171)
Firm controls						
Worker controls	✓	✓	✓	✓	✓	✓
Hierarchy FE	✓			✓		
Firm FE	✓			✓		
Firm × Hierarchy FE		✓			✓	
Firm × Hierarchy FE × Occupation FE			✓			✓
Market FE	✓	✓	✓	✓	✓	✓
Industry FE						
Observations	105,349	104,857	77,366	105,349	104,857	77,366

s.e. clustered at the local labor market × industry level

Table A4: estimation results, equations (8), (9) and (10); the dependent variable is *General Intensity* in Panel A, $\mathbb{I}(General)$ in Panel B

	(1)	(2)	(3)	(4)
Panel A				
DEP.VAR.	*Gen.Int.*	*Gen.Int.*	*Gen.Int.*	*Gen.Int.*
External Competition	-0.352*	-0.290*		
	(0.181)	(0.150)		
Internal Competition	-0.00543	-0.00824		
	(0.0214)	(0.0202)		
Share of External Competitors			-0.458**	-0.357**
			(0.201)	(0.171)
Panel B				
DEP.VAR.	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$
External Competition	-0.423**	-0.380**		
	(0.198)	(0.183)		
Internal Competition	-0.00902	-0.00676		
	(0.0214)	(0.0206)		
Share of External Competitors			-0.511**	-0.478**
			(0.218)	(0.209)
Firm controls	✓	✓	✓	✓
Worker controls	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Hierarchy × Occupation FE		✓		✓
Firm FE				
Market FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	165,885	128,141	165,885	128,141

s.e. clustered at the local labor market × industry level

Table A5: estimation results, equations 6 and 7; the dependent variable is *General Intensity* in Panel A, $\mathbb{I}(General)$ in Panel B

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A			
DEP.VAR.	Gen.Int.	Gen.Int.	Gen.Int.	Gen.Int.	Gen.Int.	Gen.Int.
External Competition	-0.311*	-0.489***	-0.236***			
	(0.173)	(0.161)	(0.0868)			
Internal Competition	-0.0107	-0.0115	-0.00704			
	(0.0115)	(0.0101)	(0.00937)			
Share of External Competitors				-0.366	-0.597***	-0.282***
				(0.225)	(0.212)	(0.102)
			Panel B			
DEP.VAR.	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$
External Competition	-0.407**	-0.595***	-0.249**			
	(0.203)	(0.194)	(0.102)			
Internal Competitoin	-0.00316	-0.00432	-0.000192			
	(0.0117)	(0.0107)	(0.00994)			
Share of External Competitors				-0.529**	-0.772***	-0.335***
				(0.253)	(0.247)	(0.117)
Firm controls						
Worker controls	✓	✓	✓	✓	✓	✓
Hierarchy FE	✓			✓		
Firm FE	✓			✓		
Firm × Hierarchy FE		✓			✓	
Firm × Hierarchy FE × Occupation FE			✓			✓
Market FE	✓	✓	✓	✓	✓	✓
Industry FE						
Observations	113,580	113,061	80,843	113,580	113,061	80,843

s.e. clustered at the local labor market × industry level

Table A6: estimation results, equations (8), (9) and (10); the dependent variable is *General Intensity* in Panel A, $\mathbb{I}(General)$ in Panel B

	(1)	(2)	(3)	(4)
Panel A				
DEP.VAR.	Gen.Intensity	Gen.Intensity	Gen.Intensity	Gen.Intensity
External Competition	-0.331*	-0.317**		
	(0.169)	(0.156)		
Internal Competition	0.000169	0.000106		
	(0.0155)	(0.0145)		
Share of External Competitors			-0.396***	-0.379***
			(0.147)	(0.136)
Panel B				
DEP.VAR.	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$
External Competition	-0.315*	-0.292*		
	(0.181)	(0.171)		
Internal Competition	-0.00403	0.000266		
	(0.0171)	(0.0157)		
Share of External Competitors			-0.340**	-0.358**
			(0.160)	(0.151)
Firm controls	✓	✓	✓	✓
Worker controls	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Hierarchy × Occupation FE		✓		✓
Firm FE				
Market FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	188,443	144,719	188,443	144,719

s.e. clustered at the local labor market × industry level

Table A7: estimation results, equations 6 and 7. The independent variable is the number of firms, weighted by employment.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
DEP.VAR.	Gen.Int.	Gen.Int.	Gen.Int.	Gen.Int.	Gen.Int.	Gen.Int.
External Competition	-0.233	-0.298*	-0.00153			
	(0.168)	(0.178)	(0.107)			
Internal Competition	-0.00929	-0.00965	-0.00224			
	(0.0104)	(0.0101)	(0.00679)			
Share of External Competitors				-0.180	-0.254*	0.0279
				(0.147)	(0.148)	(0.0959)
Panel B						
DEP.VAR.	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$
External Competition	-0.231	-0.287	-0.00556			
	(0.223)	(0.237)	(0.144)			
Internal Competition	-0.0147	-0.0128	-0.00476			
	(0.0133)	(0.0133)	(0.00859)			
Share of External Competitors				-0.117	-0.203	0.0478
				(0.184)	(0.189)	(0.124)
Firm controls						
Worker controls	✓	✓	✓	✓	✓	✓
Hierarchy FE	✓			✓		
Firm FE	✓			✓		
Firm × Hierarchy FE		✓			✓	
Firm × Hierarchy FE × Occupation FE			✓			✓
Market FE	✓	✓	✓	✓	✓	✓
Industry FE						
Observations	128,349	127,817	90,700	128,349	127,817	90,700

s.e. clustered at the local market × industry level

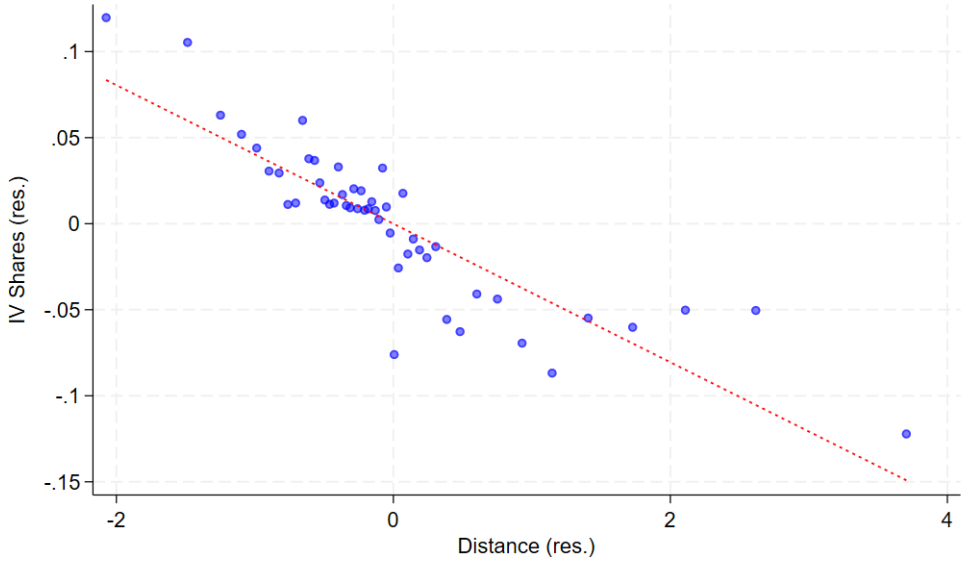
Table A8: estimation results, equations (8), (9) and (10). The independent variable is the number of firms, weighted by employment.

A.5 Validating the Exogeneity of the Instrument Shares

We want to show that the shares are driven by **long-run, structural constraints**, rather than **strategic or endogenous choices** by firms. We do so by running the following regression:

$$Share_{m,n,2015} = \rho_0 + \rho_1 Distance_{m,n} + \mu_m + \mu_n + \epsilon_{m,n}$$

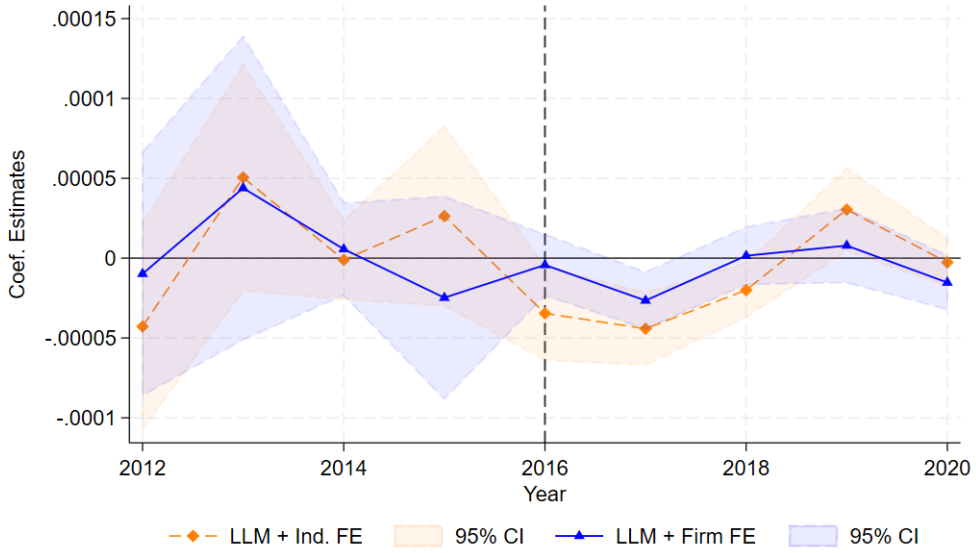
In the figure below, we plot a binscatter of the residualized 2015 shares against our distance measure. Distance + Origin & Destination FE explain $\approx 68\%$ of the share variation. This suggests indeed that most of the variation in the shares is driven by time-invariant factors, that are unlikely to affect firms' time-varying training decisions. Next, we provide additional



Binned scatterplot of the residualized 2015 shares against the residualized Distance. Both variables are standardized.

evidence on the exogeneity of the shares by performing a *placebo* analysis: if the 2015 shares are exogenous, they should not predict training decisions before the relevant demand shocks occur. We run the following regression, and plot the coefficient estimates for β_1 in the figure below.

$$\overline{\sigma}_{i,j,l,t} = \beta_0 + \beta_1 IV_{2016} \times \mathbb{I}(year = t) + \gamma_j + \gamma_l + \epsilon_{i,j,l,t}$$



Event study coefficients for the regression of the average similarity score on the IV constructed using the 2016 Shifts

As shown in the figure, the IV constructed using the 2016 Shifts correlates with training generality only in later years. Most significant effects materialize one year after the shock, justifying our choice to lag the competition measure in the empirical analysis. The fact that the coefficient estimates are never stastically different from zero in the pre-period confirms our hypothesis that the 2015 shares can be taken as exogenous.

A.6 Section 4: Tables

	Generality Score	Year	N.Employees	N.years	N.locations per firm
Mean	.027	2016.77	142.371	2.573	7.871
Count	72,892	72,892	72,845	72,892	72,892
Min	0	2012	0	1	1
p10	.007	2013	5	1	1
p25	.0144	2014	12	1	1
p50	.025	2017	36	2	1
p75	.038	2019	104	3	3
p90	.05145	2020	265	5	20
Max	.099	2021	22,803	10	144

Table A9: Summary statistics of the main establishment-level variables. The generality score is the average cosine similarity of tf-idf vectors. Employment refers to the last recorded year for each establishment.

A.7 Figures

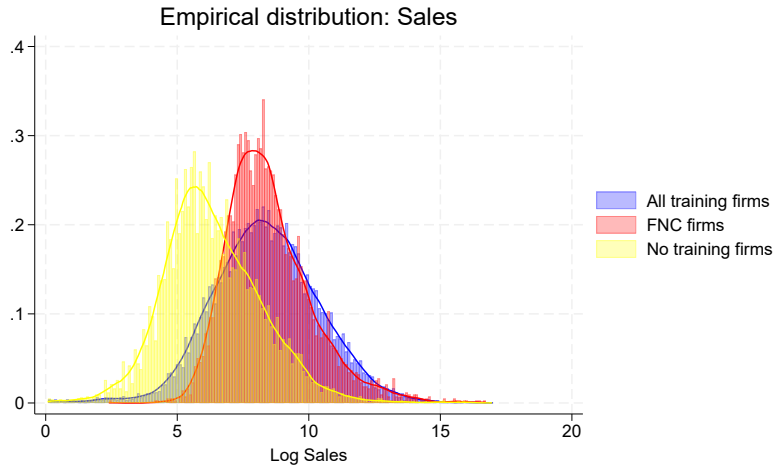


Figure 8: Empirical distribution of log(Sales) for: all RIL firms that train at least one of their employees (in blue); all FNC firms in our baseline sample (red); all RIL firms that do not train any employee (yellow).

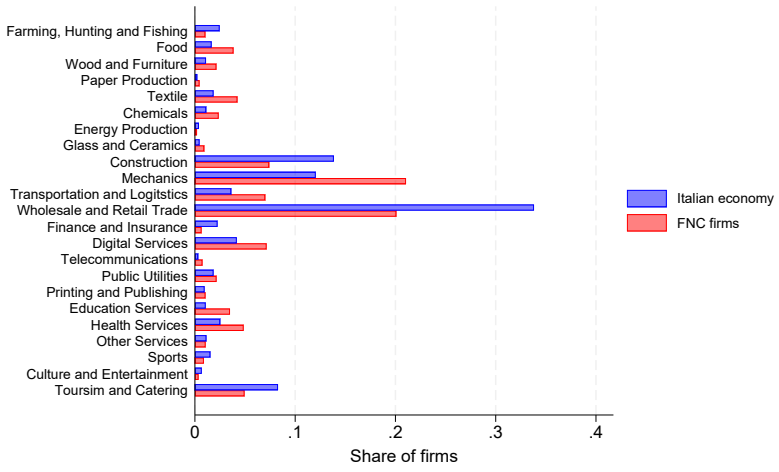


Figure 9: Distribution of firms across industrial sectors for FNC firms and for all other firms in the Italian economy

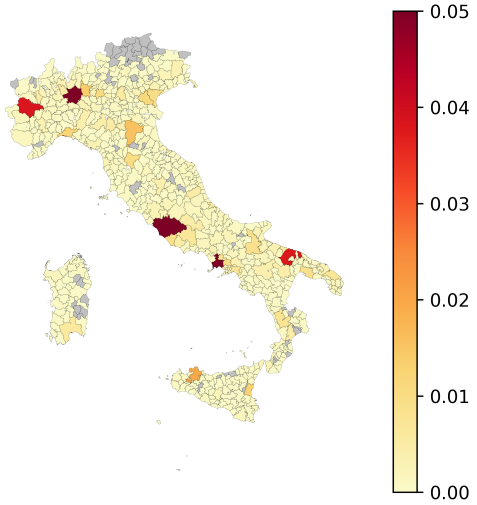


Figure 10: Average share of workers trained in each commuting zone

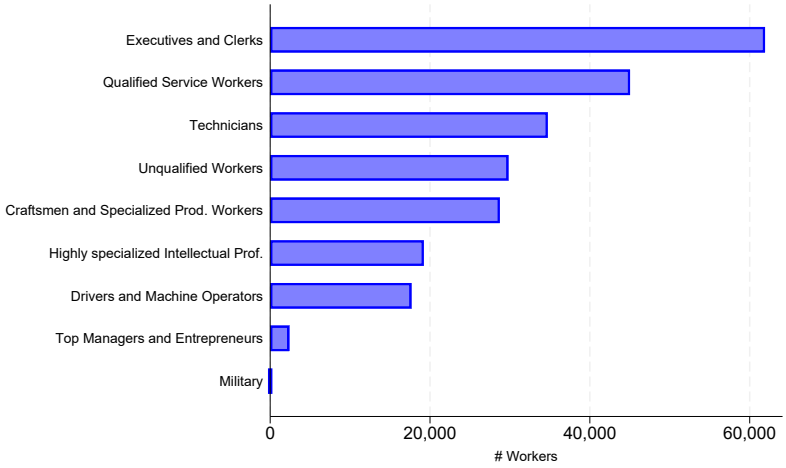


Figure 11: Number of workers for each 1-digit occupation cluster

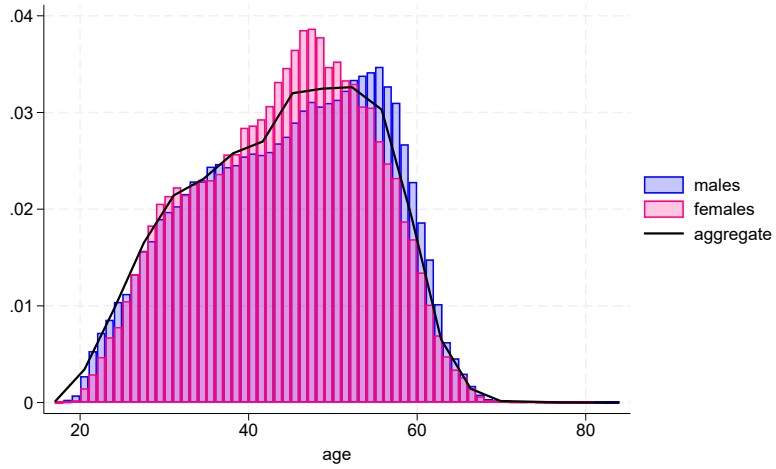


Figure 12: Age distribution for the populations of male and female workers

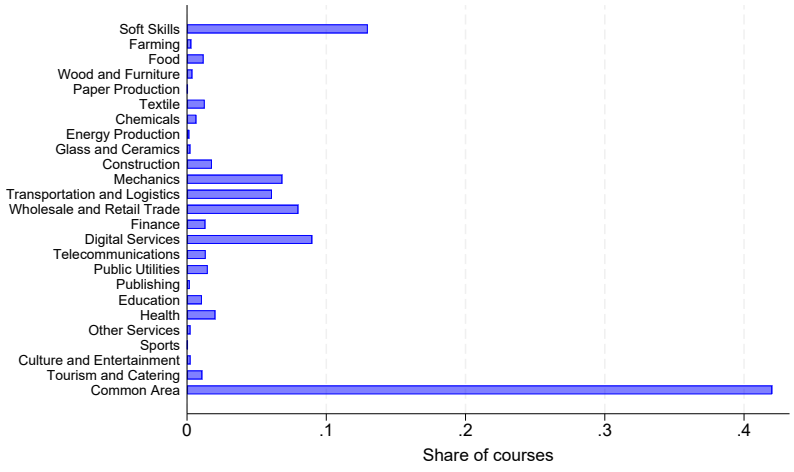


Figure 13: Distribution of courses across industrial categories, classified using INAPP's *Work Atlas* taxonomy

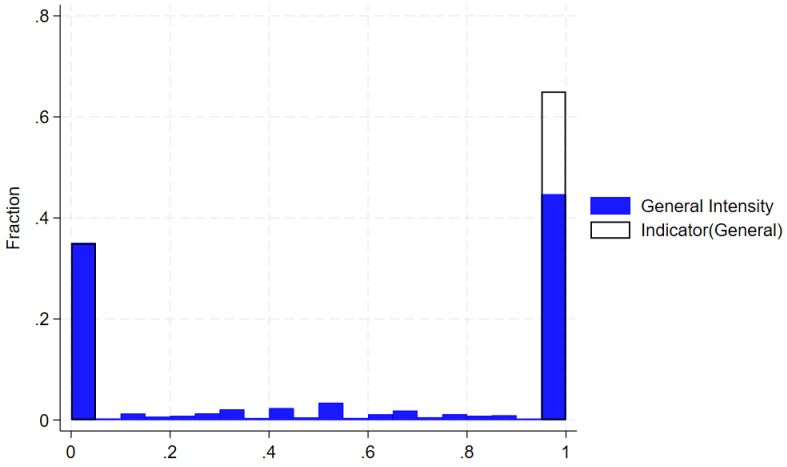


Figure 14: Empirical distribution function of the two outcome variables

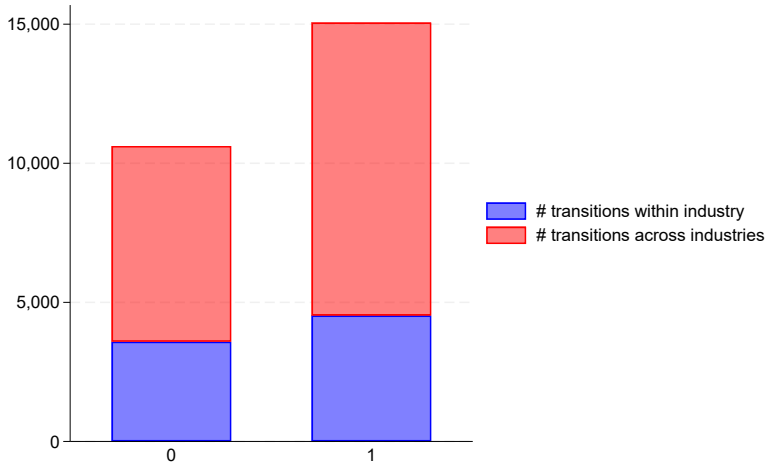


Figure 15: Number of voluntary E to E transitions for workers that did not receive any general training (0) and for those who did (1).

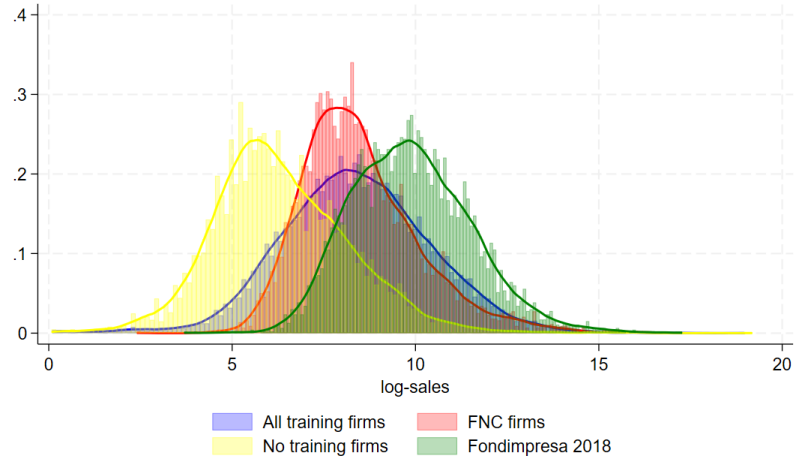


Figure 16: Empirical distribution of log(Sales) in the year 2018 for: all RIL firms that train at least one of their employees (in blue); all FNC firms in our baseline sample (red); all RIL firms that do not train any employee (red); all firms in the Fondimpresa sample for 2018 (green)

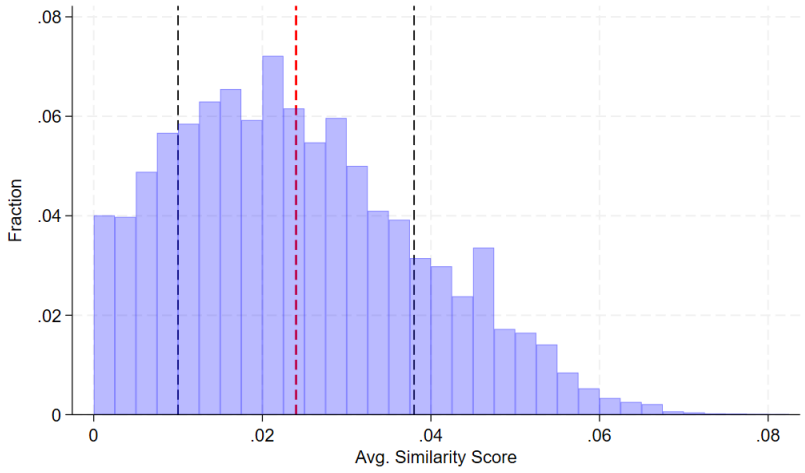


Figure 17: Empirical Distribution of the average similarity score. The red vertical line corresponds to the mean level, while the dark vertical lines indicate 1 s.d. differences from the mean

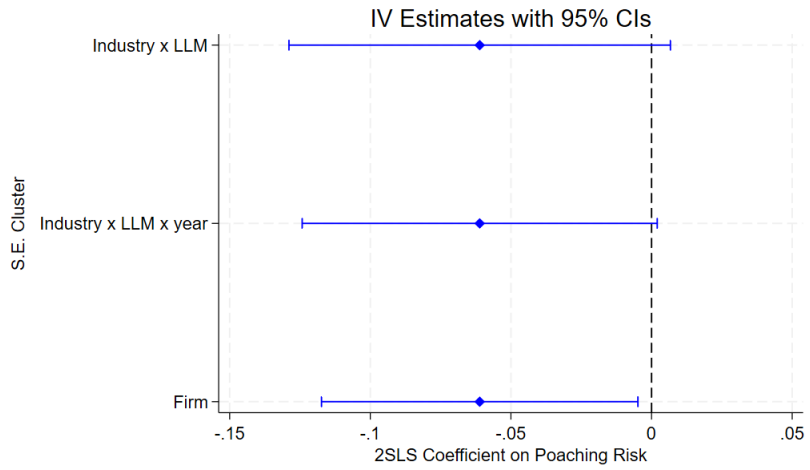


Figure 18: IV 2SLS coefficient estimates for different S.E. cluster choices