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

Mattia Albanese, Manfredi Aliberti *

Rome Economics Doctorate (EIEF, Tor Vergata and LUISS)

April 2025

Abstract

Skills acquired on the job, whether general or industry-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 a recent policy intervention in the Italian labor market, we develop a new measure that captures the tasks taught in firm-provided training for individual workers. This measure enables us to examine the relationship between labor market competition and firms' decisions to invest in general versus industry-specific skills. Our findings indicate that, as theory predicts, workers in more competitive labor markets receive less general training.

*We are deeply grateful to the personnel at INAPP, Ministero del Lavoro, ANPAL, Sviluppo Lavoro Italia for their invaluable assistance in data collection and policy insights, particularly Davide Premutico, Alessandra Biancolini, Pasquale Mauro, Luca Mattei, Raffaele Tangorra, Pietro Orazio Ferlito, and Barbara Rossi. We also extend our gratitude to our supervisors, Emanuele Tarantino and Fabiano Schivardi, as well as the LUISS, EIEF, and Tor Vergata faculty, including Liangjie Wu, Mounu Prem, Matteo Paradisi, Stefano Gagliarducci, Emilio Calvano, Claudio Michelacci, Daniele Terlizzese, Massimo Sbracia, and Facundo Piguillem, for their continued support. Special thanks go to Samuel Bentolila, Jeremy Pearce, Claudia Macaluso, and Vincenzo Pezone for their valuable feedback. The views expressed in this paper are solely those of the authors and do not represent the opinions of the affiliated institutions, INAPP, Ministero del Lavoro, ANPAL, Sviluppo Lavoro Italia, or Fondimpresa. Any errors are our own.

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 a recent policy enacted by the Italian government to examine how local labor market competition affects firms' propensity to invest in general versus industry-specific skills. The granularity of the data collected through the policy 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 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.

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]

[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

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.

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 workers across firms and industries. It enables us to identify the appropriate measure of competition when employers choose between industry-specific and fully general training: the share of establishments located in a worker's local labor market that operate in different 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. We find that increasing by one standard deviation (11 percentage points) the share of local establishments in other industries lowers training content generality by approximately 7.5% with respect to the mean. We also find that the same variation leads to a 7.7% decrease in the probability that a worker receives some general training. The 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.

In the final section 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. Also in this case, we estimate a negative effect of competition on the provision of general training. Hence, this additional exercise corroborates the evidence produced in the first part of the paper.

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 describes the policy and the data used in the analysis; Section 3 presents the theoretical model to convey the primary intuitions behind the mechanisms we test; Section 4 outlines the empirical methodology employed to test our main hypotheses and reports the results; Section 5 details the analysis conducted on the *Fondimpresa* data; and Section 6 concludes the paper while outlining potential avenues for future research.

2 Institutional Framework and Data

2.1 Institutional Framework: Fondo Nuove Competenze

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.

Firms' Balance Sheet Information

Our source for firm-level balance sheet data is the AIDA[6] 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 7,704 firms and 335,967 workers from the 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

[6] Analisi Informatizzata delle Aziende Italiane

match 251,465 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.

2.2 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 1 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 1 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 1 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.

Table 1 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 3, 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.[7] The figure suggests that the FNC sample is

[7]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

	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 1: 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.

representative of the population of training firms in Italy.

As shown in Figure 4, recipient firms span a large number of industrial sectors, defined according to the taxonomy provided by INAPP's *Work Atlas*[8]: 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 paper, 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 sector, the average firms tends to be smaller, and, as shown in Figure 3, 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 5).

Workers

Looking at the workers trained through the *Fondo Nuove Competenze*, our sample is characterized by large heterogeneity, along multiple dimensions: occupation, the hierarchical

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

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 2 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.

Hierarchy		**Contract Type**		**Contract Duration**	
Apprentice	12,618	Full-time	263,386	Permanent	317,082
Production worker	124,946	Part-time	72,581	Temporary	18,178
Clerk	169,797			Seasonal	707
Middle manager	21,472				
Top manager	3,205				
Other	543				

Table 2: Contract-level characteristics of trained workers

In terms of demographics, 36% of our sample is made up by female workers. The average worker is 44 years old. Appendix Figure 7 reports the age distribution of the workers of our sample by gender.

2.3 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 8 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 9 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 3 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 3, 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.

	General Intensity		$\mathbb{I}$(General)		
	mean	median	mean	median	N
Panel A: Gender					
Male	0.49	0.5	0.58	1	152,508
Female	0.59	0.83	0.7	1	89,500
Panel B: Age					
<30	0.45	0.33	0.55	1	28,367
30-45	0.51	0.54	0.61	1	105,586
45-57	0.55	0.66	0.65	1	86,205
>57	0.57	0.8	0.66	1	21,850
Panel C: Hierarchy					
Apprentice	0.49	0.5	0.58	1	9,967
Prod. worker	0.39	0	0.47	0	98,368
Clerk	0.60	0.8	0.726	1	111,835
Middle manager	0.8	1	0.88	1	16,091
Upper manager	0.85	1	0.92	1	2,687
Panel D: Occupation					
Executives and clerks	0.69	1	0.8	1	41,235
Qualified service workers	0.37	0	0.48	0	37,123
Technicians	0.62	1	0.71	1	26,669
Unqualified workers	0.41	0	0.5	0	24,267
Craftsmen	0.36	0	0.45	0	21,696
Intellectual professions	0.65	1	0.73	1	14,944
Drivers and machine operators	0.34	0	0.44	0	14,154
Top managers and entrepreneurs	0.60	0.82	0.69	1	1,886

Table 3: Mean, median and count of the outcome variables across workers' types

3 Theoretical Model

Before entering the core of the empirical analysis, we lay out a simple theoretical model of firms' investment in general versus industry-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.

3.1 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 industry. 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 $f(g, 0)$.

3.2 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.

3.3 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:

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

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.

3.4 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 next section, we will show how we can use fixed effects and unique features of our data to identify the relevant comparisons.

4 Empirical Analysis

4.1 Relevant Competition Measures

In Section 2, we defined a new measure of training content generality. In this Section, 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*,[9] 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 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 $k(j)$

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

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.[10] 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 4 reports descriptive statistics for the three variables, collapsed at the *Industry* $\times$ *Local Labor Market* level.

	$log\ N_{-k(j),m(i)}$	$log\ N_{k(j),m(i)}$	$Sh_{k(j),m(i)}$
Mean	9.09	5.36	.941
Min	5.77	0	.374
p25	8.37	4.06	.922
Median	9.01	5.35	.981
p75	9.65	6.63	.993
Max	12.95	11.53	.999
N	3482	3482	3482

Table 4: key moments of the distribution of the 3 competition measures

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

4.2 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:

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

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 × 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 1,325 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 × hierarchy level, as in equation (9), and at the firm × hierarchy × 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.

4.3 Results

Tables 5 and 6 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 5, 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 5, one standard deviation increase in the share of external competitors (which is approximately 0.095) lowers workers' general intensity score by 5.5 percentage points on average. Considering that the mean of the dependent variable is 0.468, this maps into a 12% reduction of the general intensity, for observations around the mean.

We find similar estimates when we use $\mathbb{I}(General)$ as the dependent variable. Looking at Table 6, 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 measures of external

	(1)	(2)	(3)	(4)
DEP.VAR.	*Gen.Int.*	*Gen.Int.*	*Gen.Int.*	*Gen.Int.*
External Competition	-0.470**	-0.462***		
	(0.183)	(0.142)		
Internal Competition	-0.005	-0.002		
	(0.028)	(0.027)		
Share of External Competitors			-0.596**	-0.618***
			(0.229)	(0.165)
Mean(Dep.Var.)	0.468	0.450	0.468	0.450
Firm controls	✓	✓	✓	✓
Worker controls	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Hierarchy × Occupation FE		✓		✓
Firm FE				
Market FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	177,967	135,910	177,967	135,910
R-squared	0.230	0.264	0.230	0.264

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

Table 5: estimation results, equations 5 and 6; 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

competition.

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 7 report the coefficient estimates when the main independent variable is the log-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 (11 percentage points) the share of local establishments in other industries lowers training content generality

	(1)	(2)	(3)	(4)
DEP.VAR.	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$
External Competition	-0.582***	-0.582***		
	(0.166)	(0.152)		
Internal Competition	-0.017	-0.007		
	(0.030)	(0.029)		
Share of External Competitors			-0.638***	-0.721***
			(0.202)	(0.166)
Mean(Dep.Var.)	0.577	0.555	0.577	0.555
Firm controls	✓	✓	✓	✓
Worker controls	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Hierarchy × Occupation FE		✓		✓
Firm FE				
Market FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	177,967	135,910	177,967	135,910
R-squared	0.264	0.275	0.264	0.275

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

Table 6: estimation results, equations 5 and 6; 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.

by approximately 7.5% with respect to the mean. Table 8 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 7.7% with respect to the mean, in the 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 never statistically significant. 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 benefits from knowledge externalities, due to the existence industrial

DEP.VAR.	(1) Gen.Int.	(2) Gen.Int.	(3) Gen.Int.	(4) Gen.Int.	(5) Gen.Int.	(6) Gen.Int.
External Competition	-0.331**	-0.535***	-0.266**			
	(0.149)	(0.131)	(0.0997)			
Internal Competition	-0.002	-0.010	-0.015			
	(0.017)	(0.013)	(0.019)			
Share of External				-0.439***	-0.670***	-0.304***
Competitors				(0.147)	(0.153)	(0.103)
Mean(Dep.Var.)	0.470	0.470	0.442	0.470	0.470	0.442
Firm controls						
Worker controls	✓	✓	✓	✓	✓	✓
Hierarchy FE	✓			✓		
Firm FE	✓			✓		
Firm × Hierarchy FE		✓			✓	
Firm × Hierarchy FE						
× Occupation FE			✓			✓
Market FE	✓	✓	✓	✓	✓	✓
Industry FE						
Observations	107,130	106,679	76,259	107,130	106,679	76,259
R-squared	0.720	0.760	0.820	0.720	0.760	0.820

s.e clustered at the labor market × industry level

Table 7: estimation results, equations 7, 8 and 9; 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.

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.

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.

Brunello and Gambarotto 2007 identify agglomeration economies as another potential

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	-0.550**	-0.745***	-0.356**			
	(0.226)	(0.225)	(0.156)			
Internal Competition	-0.010	-0.016	-0.021			
	(0.017)	(0.014)	(0.023)			
Share of External Competitors				-0.676** (0.252)	-0.910*** (0.271)	-0.394** (0.176)
Mean(Dep.Var.)	0.587	0.587	0.557	0.587	0.587	0.557
Firm controls						
Worker controls	✓	✓	✓	✓	✓	✓
Hierarchy FE	✓			✓		
Firm FE	✓			✓		
Firm × Hierarchy FE		✓			✓	
Firm × Hierarchy FE × Occupation FE			✓			✓
Market FE	✓	✓	✓	✓	✓	✓
Industry FE						
Observations	107,130	106,679	76,259	107,130	106,679	76,259
R-squared	0.722	0.757	0.812	0.722	0.757	0.812

s.e clustered at the labor market × industry level

Table 8: estimation results, equations (7) and (8) and (9); 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.

determinant of firms' training intensity. Indeed, the existence of agglomeration economies increases the returns from complementarity between skilled workers and increases the incentives 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 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.

4.4 Heterogeneity Analysis

This section provides further evidence of the robustness of the mechanism behind our main results. We use information on the hierarchical level and tenure of trained workers to estimate the heterogeneity in firms' response to local competition based on workers' characteristics.

As the main trade-off behind firms' training strategy is increasing workers' productivity limiting the probability that other firms might poach them, we exploit trained workers' characteristics to assess if firms are more responsive to local competition for workers with a higher chance of mobility.

In the case of tenure, we would expect a U-shaped response. Indeed, as workers who have just been hired are less likely to be already looking for other positions, workers with higher tenure might have a higher cost of firm mobility. We estimate these effects interacting tenure dummy variables with our measure of competition in equations 8, 9, and 10.

Figure 1 shows the effects of local competition on training generality by different tenures for the trained workers estimated through equation 10. Tenure is calculated in years and all workers with 10 years or more of tenure are grouped together. The results show that firms respond to competition when choosing training regardless of workers' tenure but that the response is stronger in the case of workers who have spent few years in the firm. This result further supports the idea that firms choose their training strategy based on the trade-off between increasing workers' productivity and limiting the probability of poaching from other firms. Table A7 displays the full set of results.

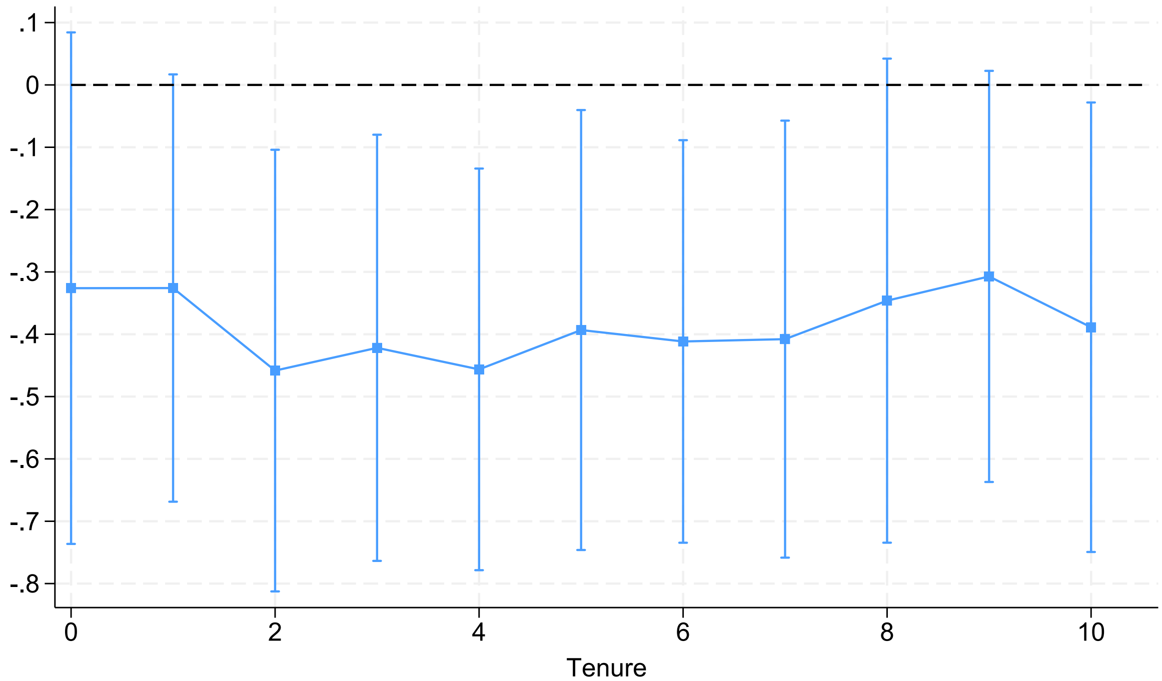

Figure 1: Effects of Competition on Training Strategy by Workers' Tenure

We further test the main rationale behind our mechanism exploiting the differences in hierarchy among trained workers. We use Italian contractual definitions to divide our workers into 5 categories: apprentices, production workers, clerks, middle managers, and upper managers. Based on our mechanism, we expect differential responses across these categories: apprentices and production workers should not respond to competition as the former should have training programs tailored to the specific occupation and the latter should have low returns to general human capital. White-collar workers and middle managers might significantly improve their outside options through general training and, thus, firms might be more responsive to competition for these categories. For what concerns upper managers, stronger competition affects their chances of leaving the firm but, in the face of stronger labor market competition, training them in HR-related skills (part of the general skills set) might give high enough returns to make it profitable to train them more in general skills.

Figure 2 shows the results of estimating equation 10 interacting dummy variables for the hierarchy level with the competition measure. In line with our expectations, we see that firms respond the most to competition in the case of clerks and middle management as they consistently exhibit significant and negative effects. The results for production workers and apprentices are not significant and thus support our prior on the absence of response to competition for these categories' training. The estimates of the response for upper management training indicate that there might be some response from firms in increasing the general training for upper management in the face of stronger labor market competition. Table A8 shows the full set of results, with additional estimations from equations 8 and 9.

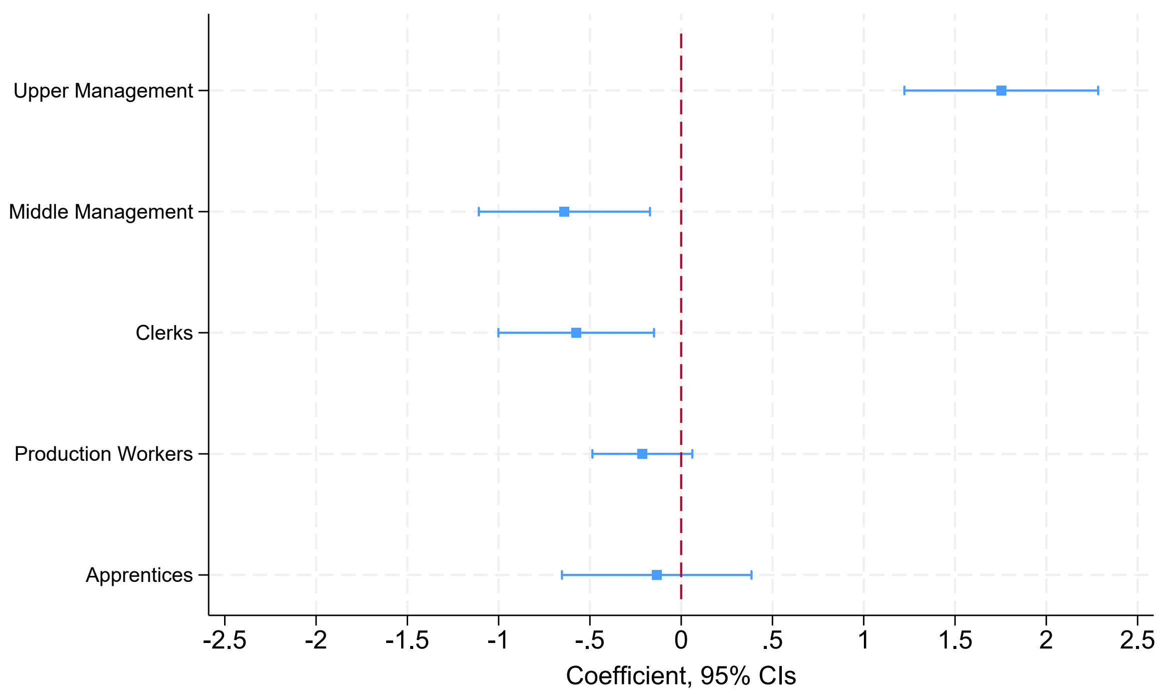

Figure 2: Effects of Competition on Training Strategy by Workers' Level

5 Robustness Checks using Fondimpresa Data

One potential limitation of the results obtained so far is that the firms used in the FNC sample have self-selected into the policy. Despite the large amount of granular worker-level and firm-level information we control for, one could still be worried that the validity of our results does not extend beyond the scope of the FNC firms. To limit this concern, we collect establishment-year level information for firms financed by the largest inter-professional fund: *Fondimpresa*. The use of this dataset also lets us exploit the time dimension to estimate exogenous variations in local labor market competition through a Bartik instrument.

Inter-professional funds are the main instrument that Italian firms use to finance the development of training projects: they were founded in the year 2000 and are administered by representatives of workers' and employers' associations. They receive money from the central government, levied via a worker-level tax that every firm is mandated to pay, corresponding to about 0.30% of a worker's yearly salary. Their task is to redistribute these funds to firms, under the condition that the funds can be used to finance training projects only.

Fondimpresa is the largest among all inter-professional funds, responsible for about 210,000 firms and 4,900,000 workers. Inter-professional funds usually distribute their funds through two main channels: the largest is the individual training account of each firm (in Italian, *Conto Formazione*), which allows firms to recover the exact amount of money that was levied by the government-mandated tax; the second channel is through specific calls for applications, in which a large grant is made available for firms who have to compete by proposing training projects meeting certain requirements.

5.1 Data and Descriptives

Firms

For this project, we have access to establishment-level data for all the training projects financed by Fondimpresa via the *Conto di Formazione* channel in the time-span 2011-2023, with the exclusion of those projects devoted to mandatory work safety training. We exploit the time dimension of the dataset to construct a Bartik instrument for our dependent variable and propose a dynamic version of specifications (8) and (9) from Section 4.

Since we are interested in studying firms' decisions about what type of training to provide as local labor market conditions change, we have willingly excluded the projects that are financed via the topic-based calls for applications, where the grant issuer specifies several requirements on the training type. This choice comes at the cost of limiting the analysis to firms that are substantially larger than those that applied to FNC. As shown in Table 9, the firms included in the *Fondimpresa* sample count are substantially larger than both the rest of the firms in the Italian economy, and the firms that applied to FNC. Figure 11 further shows that firms in the *Fondimpresa* sample are larger than average by plotting their distribution of sales against the FNC and RIL samples.

Measurement of Training Content Generality

In order to design a test for our research question, we first need to define a precise measure of training content generality. For the *Fondimpresa* data we have access to a short textual description of each training day realized by each establishment in a given year. Since we also know what is the number of workers of an establishment attending each specific training day, we produce an establishment-level measure of training content generality by implementing the following algorithm:

	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 9: The table shows summary statistics of the main balance-sheet variables for *Fondimpresa* firms, FNC firms, and the rest of Italian firms. Monetary variables are measured in millions of Euros. The difference in means reported comes from a linear regression of the variables against an indicator for belonging to the *Fondimpresa* sample; any discrepancy with a simple difference in the means reported is due to the same firms belonging to multiple samples.

1. We construct a tf-idf (*term frequency - inverse document frequency*) vector of words used in each establishment in a given year, weighted by the number of workers attending each class. Doing so, we implicitly attribute greater importance to distinctive words, that are present in one document many times, but few times in all the other documents;

2. We measure the cosine similarity of each vector to all other establishments' vectors;

3. For each establishment, we average across all cosine similarities.

We hence take the average cosine similarity score as our baseline measure of training content generality: if the words used by an establishment are also frequently encountered in the training descriptions of other establishments, we consider it as general training.

Differently from the generality measure constructed using the FNC data, we cannot distinguish between fully-general and industry-specific training classes, since the training description provided to *Fondimpresa* does not include ADA classification codes. As a consequence of that, we also change our measure of local labor market competition, aggregating the count of establishments at the level of each local labor market. Table 10 displays key summary statistics for the variables we use in the analysis: the unit of observation corresponds to an individual establishment.

	Generality Score	Year	N.Employees	N.years	N.locations per firm	log(N.establishments) in the same local market
Mean	.027	2016.77	142.371	2.573	7.871	10.221
Count	72,892	72,892	72,845	72,892	72,892	72,892
Min	0	2012	0	1	1	0
p10	.007	2013	5	1	1	8.366
p25	.0144	2014	12	1	1	9.024
p50	.025	2017	36	2	1	10.124
p75	.038	2019	104	3	3	11.206
p90	.05145	2020	265	5	20	12.861
Max	.099	2021	22,803	10	144	12.945

Table 10: Key moments of the distributions of the main establishment-level variables. The generality score is computed using the average cosine similarity of an establishment's tf-idf vector and those of all other establishments. The number of employees refers to the last year available for an establishment. The number of years indicates the number of years for which we have information on an establishment's training content. The number of locations indicates the number of local markets in which a given firm has at least one establishment.

5.2 Empirical Analysis

To evaluate the effect of an increase in the number of competitors on the generality score of an establishment, we can replicate the empirical design of Section 4, taking establishment i, in market m at time t as the unit of observation:

$$Generality_{i,m,t} = \beta_0 + \beta_1 log(N_{m,t}) + \gamma_m + \gamma_t + \gamma_f + \epsilon_{i,m,t}$$

The parameters γ_m, γ_t and γ_f represent local market fixed effects, time fixed effects, and firm fixed effects, respectively. The fact that, differently from the analysis realized in Section 4, our sample is now a repeated cross-section allows us to address further concerns about the endogeneity of the chosen competition measure. We do so using a shift-share instrumental variable strategy (Goldsmith-Pinkham et al. 2020), exploiting exogenous changes in the *national* growth of Italian industries to shock *local* changes in the number of establishments in the market. In particular, we use aggregate sector-level data from the Italian Census, combined with information on the share of each sector's number of establishments in each local labor market in 2012, to predict the number of establishments in years post-2012:

- $\mathbf{Shift}_{st}$: national growth of ATECO 1-digit sectors (s)
- $\mathbf{Share}_{ms}^{2012}$: share of each sector's number of establishments in each local labor market in 2012
- $\mathbf{Instrument}_{mt} = \sum_s (Share_{ms}^{2012} \times Shift_{st})$

The instrument predicts the number of establishments we should see in every local market given national growth rates, assuming that the local industry shares remain constant to 2012 level. Given this instrument, we run a first stage regression of the dependent variable on the instrument:

$$log(N_{m,t}) = \alpha_0 + \alpha_1 Instrument_{m,t} + \gamma_m + \gamma_t + \epsilon_{mt} \tag{11}$$

The second stage follows:

$$Generality_{i,m,t} = \beta_0 + \beta_1 log(N_{m,t})^{IV} + \gamma_m + \gamma_t + \gamma_f + \epsilon_{i,m,t} \tag{12}$$

The identification strategy relies on the usual two assumptions: first, the instrument must be correlated with the chosen dependent variable. Second, it must affect the outcome only through the dependent variable. Among the two, the second assumption is the most demanding one, requiring that either the 2012 industry share does not affect the observed similarity in training descriptions through alternative channels, or that the national growth does not do the same. The presence of fixed effects at the market, firm and year level helps us alleviate such concerns.

Table 11 reports the results of the IV analysis. Our most restrictive specification includes year × firm fixed effects, as well as market × firm fixed effects, partialling out the effect of any firm-level trend or firm-market time-invariant effect. The coefficients are negative and significantly different from 0 at the 95% confidence level, consistent with our findings on the FNC sample. Overall, the magnitude is sizable: according to the parameter estimates from the most restrictive specification, a 1% increase in the number of competitors lowers an establishment's average generality by approximately 1.6% with respect to the mean.

DEP.VAR. METHOD	Generality OLS	Generality IV	Generality OLS	Generality IV	Generality OLS	Generality IV
Effect of Competition:						
$log(N_{m,t})$	-0.0003	-0.0170*	-0.0007*	-0.0327**	-0.00168*	-0.0436**
	(0.0006)	(0.0099)	(0.0004)	(0.0121)	(0.0009)	(0.0162)
First Stage:						
$Instrument_{m,t}$		1.5371***		1.3249***		1.384***
		(0.1558)		(0.2158)		(0.2488)
F-test		97.39		37.68		31.21
		[0.000]		[0.000]		[0.000]
Mean(Dep.Var.)	0.0272	0.0272	0.0272	0.0272	0.0272	0.0272
Market FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Year × Firm FE			✓	✓	✓	✓
Market × Firm FE					✓	✓
Observations	55,641	55,641	27,338	27,338	22,611	22,611

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

Table 11: Column (1) reports the parameter estimates for the OLS regression of the generality score on the number of local competitors. The specification includes market FE, year and firm FE. Column (2) instead repeats the same exercise, but instruments the number of competitors using the shift-share IV. The first stage coefficient, as well as the F-test are reported in rows 2 and 3. Columns (3) and (4) repeat the analogous exercise, with the addition of year × firm FE. In columns (5) and (6) we also include market × firm FE.

6 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 from different industries tend to invest more in industry-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 validate our findings 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 local labor market competition firms face. The estimates confirm the results from the main 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.

References

Acemoglu, D. and Pischke, J.-S. (1998). Why do firms train? theory and evidence. *The Quarterly journal of economics*, 113(1):79–119.

Acemoglu, D. and Pischke, J.-S. (1999). The structure of wages and investment in general training. *Journal of political economy*, 107(3):539–572.

Adda, J. and Dustmann, C. (2023). Sources of wage growth. *Journal of Political Economy*, 131(2):456–503.

Adhvaryu, A., Bassi, V., Nyshadham, A., Tamayo, J. A., and Torres, N. (2023). Organizational responses to product cycles. Technical report, National Bureau of Economic Research.

Adhvaryu, A., Kala, N., and Nyshadham, A. (2018). The skills to pay the bills: Returns to on-the-job soft skills training. Technical report, National Bureau of Economic Research.

Alfonsi, L., Bandiera, O., Bassi, V., Burgess, R., Rasul, I., Sulaiman, M., and Vitali, A. (2020). Tackling youth unemployment: Evidence from a labor market experiment in uganda. *Econometrica*, 88(6):2369–2414.

Andrieu, E., Jamet, S., Marcolin, L., and Squicciarini, M. (2019). Occupational transitions: The cost of moving to a "safe haven".

Arrow, K. J. (1962). The economic implications of learning by doing. *The review of economic studies*, 29(3):155–173.

Autor, D. H. (2001). Why do temporary help firms provide free general skills training? *The Quarterly Journal of Economics*, 116(4):1409–1448.

Azar, J., Marinescu, I., and Steinbaum, M. (2022). Labor market concentration. *Journal of Human Resources*, 57(S):S167–S199.

Barbieri, T., Basso, G., and Scicchitano, S. (2022). Italian workers at risk during the covid-19 epidemic. *Italian Economic Journal*, 8(1):175–195.

Bassi, V., Muoio, R., Porzio, T., Sen, R., and Tugume, E. (2022). Achieving scale collectively. *Econometrica*, 90(6):2937–2978.

Bassi, V. and Nansamba, A. (2022). Screening and signalling non-cognitive skills: experimental evidence from uganda. *The Economic Journal*, 132(642):471–511.

Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of political economy*, 70(5, Part 2):9–49.

Benmelech, E., Bergman, N. K., and Kim, H. (2022). Strong employers and weak employees: How does employer concentration affect wages? *Journal of Human Resources*, 57(S):S200–S250.

Bentolila, S., Cabrales, A., and Jansen, M. (2023). Does dual vocational education and training pay off?

Berger, D., Herkenhoff, K., and Mongey, S. (2022). Labor market power. *American Economic Review*, 112(4):1147–1193.

Bianchi, N. and Giorcelli, M. (2022). The dynamics and spillovers of management interventions: Evidence from the training within industry program. *Journal of Political Economy*, 130(6):1630–1675.

Brunello, G. and De Paola, M. (2008). Training and economic density: Some evidence form italian provinces. *Labour Economics*, 15(1):118–140.

Brunello, G. and Gambarotto, F. (2007). Do spatial agglomeration and local labor market competition affect employer-provided training? evidence from the uk. *Regional Science and Urban Economics*, 37(1):1–21.

Caicedo, S., Espinosa, M., and Seibold, A. (2022). Unwilling to train?—firm responses to the colombian apprenticeship regulation. *Econometrica*, 90(2):507–550.

Caldwell, S. and Danieli, O. (2024). Outside options in the labor market. *Review of Economic Studies*, page rdae006.

Caliendo, M., Cobb-Clark, D. A., Obst, C., and Uhlendorff, A. (2023). Risk preferences and training investments. *Journal of Economic Behavior & Organization*, 205:668–686.

Card, D., Cardoso, A. R., Heining, J., and Kline, P. (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics*, 36(S1):S13–S70.

Cefala, L., Naso, P., Ndayikeza, M. A., and Swanson, N. (2024). Under-training by employers in informal labor markets: Evidence from burundi.

Citino, L., Linarello, A., Lotti, F., Petrella, A., Sette, E., and Di Porto, E. (2023). Creation, destruction and reallocation of jobs in italian firms: an analysis based on administrative data. *Bank of Italy Occasional Paper*, (751).

Davis, S. J. and Haltiwanger, J. (1999). On the driving forces behind cyclical movements in employment and job reallocation. *American Economic Review*, 89(5):1234–1258.

Dietz, D. and Zwick, T. (2021). The retention effect of training: Portability, visibility, and credibility1. *The International Journal of Human Resource Management*, 33(4):710–741.

Dustmann, C. and Schönberg, U. (2002). Training and unions. Technical report, mimeo, University College London.

Eckardt, D. (2023). Training specificity and occupational mobility: Evidence from german apprenticeships. Technical report, mimeo, University of Warwick.

Gibbons, R. and Waldman, M. (2004). Task-specific human capital. *American Economic Review*, 94(2):203–207.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.

Jedwab, R., Romer, P., Islam, A. M., and Samaniego, R. (2023). Human capital accumulation at work: Estimates for the world and implications for development. *American Economic Journal: Macroeconomics*, 15(3):191–223.

Konings, J. and Vanormelingen, S. (2015). The impact of training on productivity and wages: firm-level evidence. *Review of Economics and Statistics*, 97(2):485–497.

Lazear, E. P. (2009). Firm-specific human capital: A skill-weights approach. *Journal of political economy*, 117(5):914–940.

Lipowski, C., Salomons, A., and Zierahn-Weilage, U. (2024). Expertise at work: New technologies, new skills, and worker impacts.

Loewenstein, M. A. and Spletzer, J. R. (1999). General and specific training: Evidence and implications. *Journal of Human Resources*, pages 710–733.

Ma, X., Nakab, A., and Vidart, D. (2024). Human capital investment and development: The role of on-the-job training. *Journal of Political Economy Macroeconomics*, 2(1):107–148.

Macaluso, C. (2023). Skill remoteness and post-layoff labor market outcomes.

Manning, A. (2013). *Monopsony in motion: Imperfect competition in labor markets*. Princeton University Press.

Marcato, A. (2022). Lights and shadows of employer concentration: On-the-job training and wages. Technical report, Bocconi University, mimeo.

Moen, E. R. and Rosén, Å. (2004). Does poaching distort training? *The Review of Economic Studies*, 71(4):1143–1162.

Mohrenweiser, J., Zwick, T., and Backes-Gellner, U. (2019). Poaching and firm-sponsored training. *British Journal of Industrial Relations*, 57(1):143–181.

Morin, Y. and Védrine, L. (2022). Do agglomeration economies affect firms' returns to training? evidence based on french industrial firms. *Papers in Regional Science*, 101(5):1135–1156.

Smits, W. (2007). Industry-specific or generic skills? conflicting interests of firms and workers. *Labour Economics*, 14(3):653–663.

Starr, E., Ganco, M., and Campbell, B. A. (2018). Strategic human capital management in the context of cross-industry and within-industry mobility frictions. *Strategic Management Journal*, 39(8):2226–2254.

Stevens, M. (1994). A theoretical model of on-the-job training with imperfect competition. *Oxford economic papers*, 46(4):537–562.

Yi, M., Müller, S., and Stegmaier, J. (2024). Industry mix, local labor markets, and the incidence of trade shocks. *Journal of Labor Economics*, 42(3):000–000.

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 10 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.

DEP.VAR	(1) $\mathbb{P}$(leave)	(2) $\mathbb{P}$(leave)	(3) $\mathbb{P}$(diff.sector | leave)	(4) $\mathbb{P}$(diff.sector | leave)
Gen.Intensity	-0.003		0.058***	
	(0.002)		(0.008)	
$\mathbb{I}$(General)		-0.001		0.047***
		(0.002)		(0.007)
Firm-level controls	✓	✓	✓	✓
Worker-level controls	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Location FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	141,091	141,091	25,249	25,249
R-squared	0.110	0.110	0.159	0.159

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	0.181***		-0.061	
	(0.036)		(0.049)	
$\mathbb{I}$(General)		0.095***		-0.008
		(0.033)		(0.045)
Firm-level controls	✓	✓	✓	✓
Worker-level controls	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Location FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	2,281	2,281	1,121	1,121
R-squared	0.548	0.544	0.472	0.471

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:

$$\begin{aligned}&[g] : \pi(1-\alpha)f_g = c_g \\ &[s] : \pi\gamma f_s\Omega(1-\alpha)f(g,s) + \pi(1-\alpha)f_s = c_s\end{aligned}$$

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

$$\begin{aligned}&[g] : f_g = c_g/(\pi(1-\alpha)) \\ &[s] : (\gamma f(g,s)\Omega + 1)f_s = c_s/(\pi(1-\alpha))\end{aligned}$$

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:

$$[gg]: \ \pi_g(1-\alpha)a - 2\kappa_g = 0$$

$$[gs]: \ \pi_s(1-\alpha)a = 0$$

$$[sg]: \ \pi_s(1-\alpha)a = 0$$

$$[ss]: \ (1-\alpha)\left[\pi_{ss}(ag+bs) + \pi_s b\right] + \pi_s(1-\alpha)b - 2\kappa_s = 0$$

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:

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

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

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 Empirical Analysis: Robustness Checks

Table A3 reports the estimation results for equations (5) and (6), 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.

Table A7 shows all the relevant information relative to the estimates shown in Figure 1. Table A8 reports all information related to Figure 2.

	(1)	(2)	(3)	(4)
		Panel A		
DEP.VAR.	*Gen.Int.*	*Gen.Int.*	*Gen.Int.*	*Gen.Int.*
External Competition	-0.428***	-0.3423**		
	(0.143)	(0.116)		
Internal Competition	-0.0211	-0.00884		
	(0.0274)	(0.0236)		
Share of External			-0.427**	-0.417***
Competitors			(0.189)	(0.144)
		Panel B		
DEP.VAR.	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$
External Competition	-0.582***	-0.513***		
	(0.144)	(0.131)		
Internal Competition	-0.0380	-0.0148		
	(0.0293)	(0.0246)		
Share of External			-0.488**	-0.581***
Competitors			(0.212)	(0.173)
Firm controls	✓	✓	✓	✓
Worker controls	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Hierarchy × Occupation FE		✓		✓
Firm FE				
Market FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	157,712	122,246	157,712	122,246
R-squared	0.239	0.283	0.239	0.283

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

Table A3: estimation results, equations (5) and (6); 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	-0.383*	-0.600***	-0.284**			
	(0.204)	(0.181)	(0.116)			
Internal Competition	-0.00252	-0.0159	-0.0128			
	(0.0187)	(0.0132)	(0.0185)			
Share of External Competitors				-0.507**	-0.727***	-0.317**
				(0.197)	(0.201)	(0.117)
			Panel B			
DEP.VAR	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$
External Competition	-0.633*	-0.839**	-0.395*			
	(0.309)	(0.298)	(0.191)			
Internal Competition	-0.0106	-0.0214	-0.0192			
	(0.0218)	(0.0171)	(0.026)			
Share of External Competitors				-0.790**	-1.008***	-0.451**
				(0.319)	(0.329)	(0.196)
Firm controls						
Worker controls	✓	✓	✓	✓	✓	✓
Hierarchy FE	✓			✓		
Firm FE	✓			✓		
Firm × Hierarchy FE		✓			✓	
Firm × Hierarchy FE × Occupation FE			✓			✓
Market FE	✓	✓	✓	✓	✓	✓
Industry FE						
Observations	93,423	93,004	68,269	93,423	93,004	68,269
R-squared	0.705	0.745	0.809	0.705	0.745	0.809

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

Table A4: estimation results, equations (7), (8) and (9); 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	-0.482*	-0.436*		
	(0.268)	(0.211)		
Internal Competition	-0.0273	-0.0270		
	(0.0305)	(0.0307)		
Share of External Competitors			-0.497	-0.449*
			(0.293)	(0.223)
		Panel B		
DEP.VAR.	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$
External Competition	-0.558**	-0.560***		
	(0.226)	(0.184)		
Internal Competition	-0.0196	-0.0173		
	(0.0309)	(0.0298)		
Share of External Competitors			-0.636**	-0.667***
			(0.228)	(0.185)
Firm controls	✓	✓	✓	✓
Worker controls	✓	✓	✓	✓
Hierarchy FE	✓	✓	✓	✓
Hierarchy × Occupation FE		✓		✓
Firm FE				
Market FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	156,472	120,240	156,472	120,240
R-squared	0.270	0.288	0.270	0.288

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

Table A5: estimation results, equations (5) and (6); 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	-0.237*	-0.427***	-0.227***			
	(0.118)	(0.105)	(0.0606)			
Internal Competition	-0.000911	-0.00280	-0.00322			
	(0.0117)	(0.0107)	(0.0231)			
Share of External Competitors				-0.333*	-0.575***	-0.332***
				(0.174)	(0.150)	(0.0602)
			Panel B			
DEP.VAR.	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$
External Competition	-0.384**	-0.590***	-0.243***			
	(0.159)	(0.152)	(0.0812)			
Internal Competition	0.004673	0.00248	0.00808			
	(0.0118)	(0.0103)	(0.0196)			
Share of External Competitors				-0.546**	-0.808***	-0.388***
				(0.196)	(0.191)	(0.0847)
Firm controls						
Worker controls	✓	✓	✓	✓	✓	✓
Hierarchy FE	✓			✓		
Firm FE	✓			✓		
Firm × Hierarchy FE		✓			✓	
Firm × Hierarchy FE × Occupation FE			✓			✓
Market FE	✓	✓	✓	✓	✓	✓
Industry FE						
Observations	93,337	92,898	67,096	93,337	92,898	67,096
R-squared	0.753	0.786	0.837	0.753	0.786	0.837

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

Table A6: estimation results, equations (7), (8) and (9); the dependent variable is *General Intensity* in Panel A, $\mathbb{I}(General)$ in Panel B

	(1)	(2)	(3)
DEP.VAR.	$\mathbb{I}(General)$	$\mathbb{I}(General)$	$\mathbb{I}(General)$
External Competition × Years of Tenure:			
0 yr.	-0.307	-0.537**	-0.327
	(0.232)	(0.257)	(0.209)
1 yr.s	-0.371*	-0.645***	-0.326*
	(0.206)	(0.225)	(0.175)
2 yr.s	-0.578**	-0.777***	-0.460**
	(0.208)	(0.237)	(0.181)
3 yr.s	-0.565**	-0.784***	-0.424**
	(0.205)	(0.237)	(0.174)
4 yr.s	-0.565**	-0.797***	-0.455*
	(0.205)	(0.225)	(0.165)
5 yr.s	-0.481**	-0.716***	-0.394**
	(0.215)	(0.236)	(0.180)
6 yr.s	-0.476**	-0.727***	-0.412**
	(0.188)	(0.214)	(0.165)
7 yr.s	-0.454*	-0.703***	-0.408**
	(0.233)	(0.246)	(0.179)
8 yr.s	-0.421*	-0.630**	-0.346*
	(0.226)	(0.254)	(0.198)
9 yr.s	-0.400*	-0.681***	-0.307*
	(0.222)	(0.226)	(0.168)
10+ yr.s	-0.464*	-0.757***	-0.389**
	(0.246)	(0.247)	(0.184)
Mean(Dep.Var.)	0.587	0.587	0.557
Worker controls	✓	✓	✓
Hierarchy FE	✓		
Firm FE	✓		
Firm × Hierarchy FE		✓	
Firm × Hierarchy FE × Occupation FE			✓
Market FE	✓	✓	✓
Observations	81,881	81,437	75,891
R-squared	0.727	0.763	0.820

s.e clustered at the labor market × industry level

Table A7: estimation results, equations 8, 9, and 10 where the treatment interacts with a dummy variable indicating the years of tenure of the trained workers

DEP.VAR.	(1) $\mathbb{I}(General)$	(2) $\mathbb{I}(General)$	(3) $\mathbb{I}(General)$
External Competition × Hierarchical Layer:			
Upper Management	-0.736	0.511	1.753***
	(0.631)	(0.463)	(0.271)
Middle Management	-1.296***	-0.897**	-0.640**
	(0.285)	(0.398)	(0.239)
Clerk	-0.581**	-1.282***	-0.575**
	(0.244)	(0.327)	(0.218)
Production Worker	-0.856**	-0.439**	-0.213
	(0.374)	(0.175)	(0.140)
Apprentice	-0.868***	-0.177	-0.134
	(0.251)	(0.642)	(0.265)
Mean(Dep.Var.)	0.587	0.587	0.557
Worker controls	✓	✓	✓
Hierarchy FE	✓		
Firm FE	✓		
Firm × Hierarchy FE		✓	
Firm × Hierarchy FE × Occupation FE			✓
Market FE	✓	✓	✓
Observations	106,969	106,528	76,177
R-squared	0.723	0.757	0.811

s.e clustered at the labor market × industry level

Table A8: estimation results, equations 8, 9, and 10 where the treatment interacts with a dummy variable indicating the hierarchical layer trained workers belong to

A.5 Figures

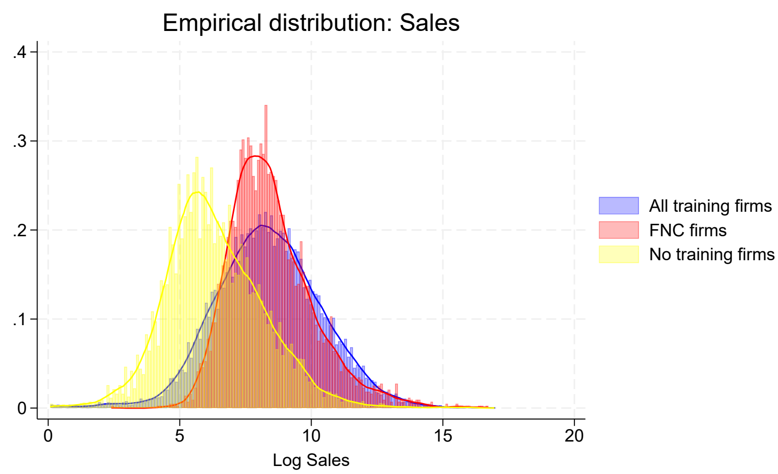

Figure 3: Empirical distribution of log(Sales) for: all RIL firms that train at least one of their employees (in blue); all FNC firms in our baseline sample (red); all RIL firms that do not train any employee (yellow).

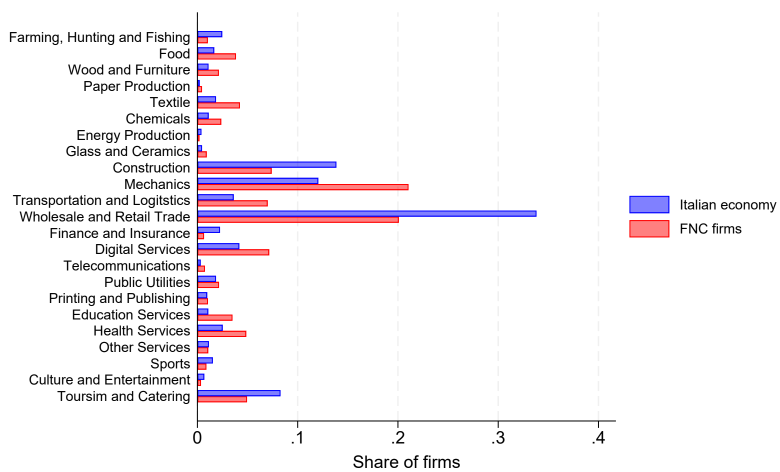

Figure 4: Distribution of firms across industrial sectors for FNC firms and for all other firms in the Italian economy

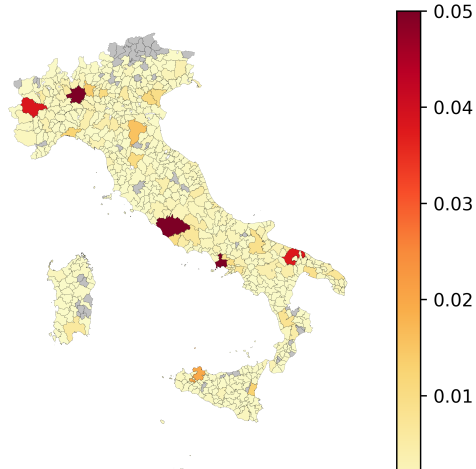

Figure 5: Average share of workers trained in each commuting zone

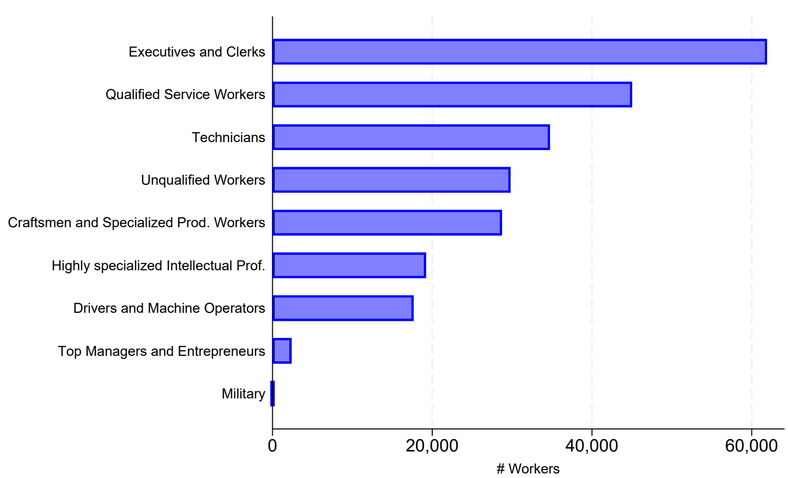

Figure 6: Number of workers for each 1-digit occupation cluster

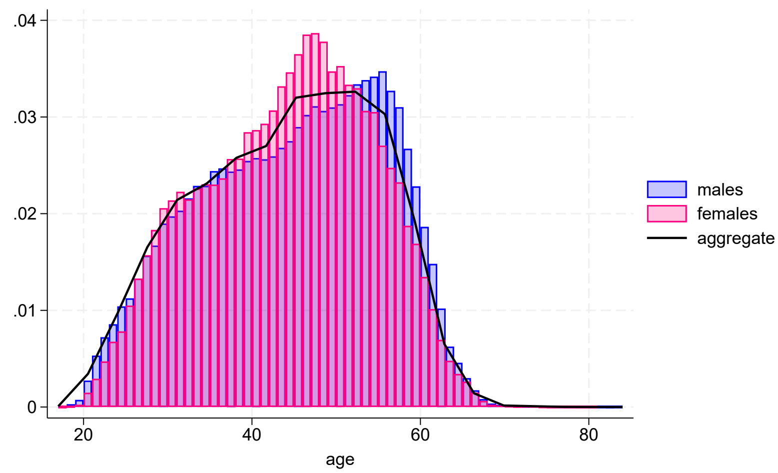

Figure 7: Age distribution for the populations of male and female workers

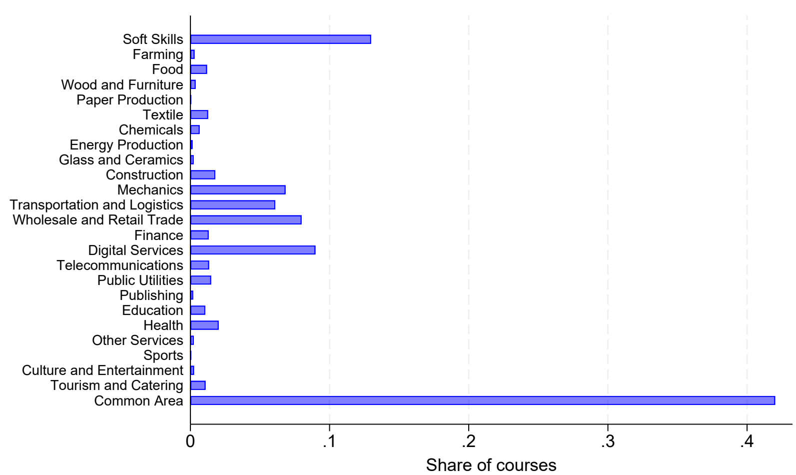

Figure 8: Distribution of courses across industrial categories, classified using INAPP's *Work Atlas* taxonomy

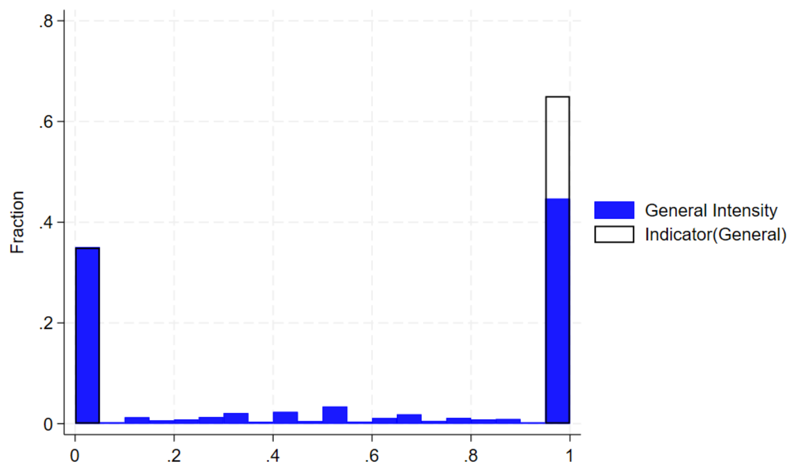

Figure 9: Empirical distribution function of the two outcome variables

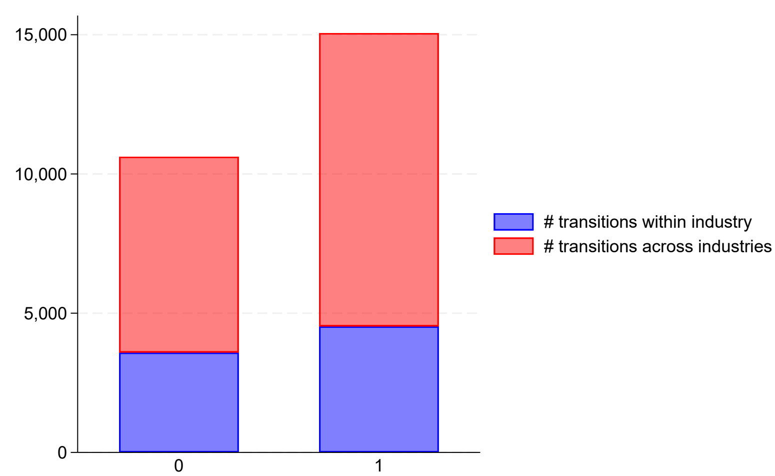

Figure 10: Number of voluntary E to E transitions for workers that did not receive any general training (0) and for those who did (1).

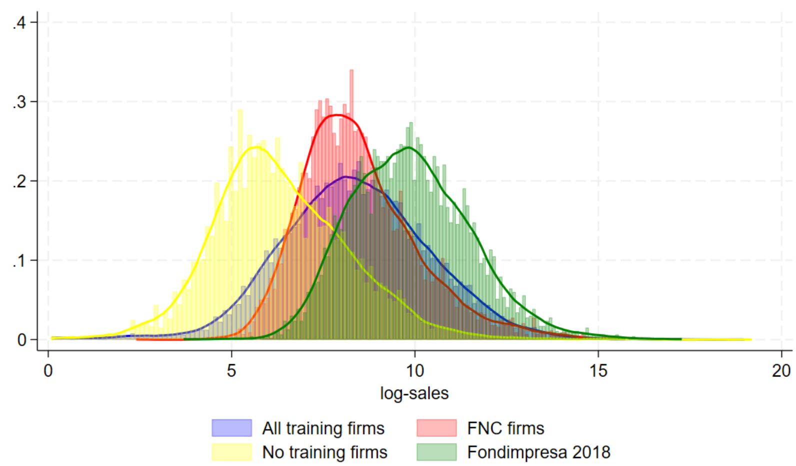

Figure 11: Empirical distribution of log(Sales) in the year 2018 for: all RIL firms that train at least one of their employees (in blue); all FNC firms in our baseline sample (red); all RIL firms that do not train any employee (red); all firms in the Fondimpresa sample for 2018 (green)