Istat

LABORATORI tematici

Progetti di ricerca tematica in Istat

Risultati della seconda call

TRAINING AND RESILIENCE: EVIDENCE FROM ITALIAN INDUSTRIAL FIRMS DURING COVID-19

ANDREA MARINO, Istat – **ELEONORA BARTOLONI,** Istat

22/23
SETTEMBRE
2025

Indice della presentazione

- Literature and research focus
- Data and outcome variables
- Empirical specification
- The provision of training and resilience: results from different estimators
- Some more results about the share of workers receiving training and the targeted skills
- Summary and conclusions
- References

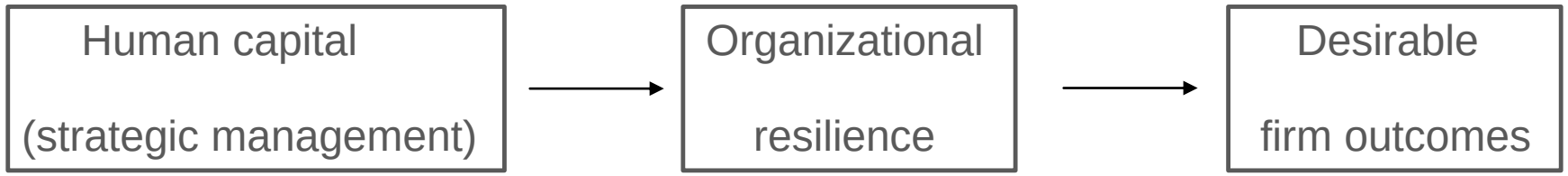
Literature and research focus (1/3)

- We contribute to a particular strand of the literature on Covid-19: **which ex-ante characteristics helped firms coping up with the impact of the first wave of the pandemic ?** (i.e. focus on the short-run impact).
- Previous contributions differ in many aspects, but a common set of relevant factors emerges.
- *Productivity* (Muzi et al., 2023…)
- *Innovation and digital technologies* (Abidi et al., 2023, Battisti, Belloc, Del Gatto, 2023,…)
- *Internationalisation* (Giglioli S. et al., 2021, Wagner, 2024…)
- *Ownership characteristics* (Amore, Pelucco and Quarato, 2022, Iborra, Lopez-Munoz and Safon, 2024…)
- *Management practices* (Grover and Karplus, 2021, Lamorgese et al., 2024, Costa et al., 2022…)
- *Finance* (Banerjee and Kharroubi, 2020…)

Literature and research focus (2/3)

- **We want to focus on human capital** and assessing its specific relevance. **In particular** we want to focus **on the role played by training**. We provide also some evidence about the role played by education level.

- Firms have to cope not only with economic shocks but also with unforeseen, potentially disruptive events of a different nature. ➔ **Human capital needed to build «*organizational resilience*»:** "*a firm's ability to effectively absorb, develop situation-specific responses to, and ultimately engage in transformative activities to capitalize on disruptive surprises that potentially threaten organization survival*" (Lengnick-Hall, et al. 2011). Similar insights from other strands of strategic management literature (e.g. Teece, 2017).



- **Empirical support for this reasoning in quite different scenarios.** Bartoloni et al. (2021): skill accumulation explains firm survival patterns in Italy in the aftermath of the Great Recession. Martinelli et al. (2024): hum.capital/organizational resilience help explain performance differences after the Emilia earthquake.

Literature and research focus (3/3)

- **Micro-level evidence on the effects of sources of skills and knowledge other than formal education was scant until a few decades ago** (due to data availability constraints and methodological difficulties).
- Mincer (1962): *"…**formal school is neither an exclusive nor a sufficient method of training the labor force**…"*. his estimates and those in Heckman et al. (1998) imply on-the-job training to account for at least 20% of human capital accumulation in the USA.
- As to training, most available analyses today concern its impact on productivity and wages. **Training and firm resilience: few results available still today** [Collier et al. (2011): higher survival for British establishments employing more educated labor and providing off-the-job training]. They provide a micro-economic framework (training ➔ labor productivity ➔ profits ➔ higher resilience).
- Some **papers on Covid-19** include training to explain resilience (e.g. Muzi et al., 2023). To the best of our knowledge, however, **this is the first contribution explicitly focusing on training and addressing endogeneity.**
- ➔ **The paper contributes also to a small but growing strand of research on the effects of training** (see Martins, 2022).

Data

- The analysis draws on **different statistical** business registers and micro-data **sources provided by** the Italian National Institute of Statistics **(Istat**)
- **ASIA Imprese**: firm-level data on key variables (economic activity, size, date of creation/cessation)
- **ASIA Occupazione**: individual-level information on worker's characteristics (sex, age, education…).
- **Frame SBS**: yearly data on structure (sector, location,..) and performance (production, sales, value added..).
- **Censimento Permanente delle Imprese (CPUE18)**: Business Census (carried out in 2019); > 200,000 enterprises with 3+ employees. Qualitative data on ownership, human capital, competitiveness, finance, innovation, internationalisation…. Data refer to the year 2018 or to the 2016-18 period.
- **"Situazione e prospettive delle imprese nell'emergenza sanitaria" (SPIESC_19)**: second Covid-19-related business survey carried out by Istat in November 2020. Provides information about the Covid-19 impact upon firms' performance and about strategies adopted to cope with the pandemic. Questions refer to the months June-October 2020. Provides us with a dataset of more than 16,000 industrial firms.

Defining Outcome and Treatment variables

- First question of the Covid-19 business survey: «*The firm is currently: a) Fully open; b) Partially open; c) Closed with re-opening plans; d) Closed without re-opening plans*».

- Our **binary outcome variable *Y*** defines **resilience** in terms of **actual operating status in Fall 2020**:

Y = 1	→	**Open firms** (regardless of whether «fully» or «partially»)
Y = 0	→	**Closed firms** (regardless of «re-opening plans»)

- NB Our outcome measure: unconventional but not new in the literature on Covid-19 (see e.g. Liu et al., 2021, and Fang et al., 2022, analyzing World Bank «*Covid-19 Follow-up Enterprise Surveys*» data). Information from «ASIA Imprese» inconsistent with the assumption that item d) = «firm exit».

- Our base **treatment (*T*) variable**: a simple **binary variable =1 for firms providing *non-mandatory training*** to their workforce **in 2018** (Business Census data) and **=0 otherwise** ➔ ***T*** is pre-determined with respect to outcome.

Sample composition

- First wave of the Covid-19 pandemic and national lockdown in march 2020 (➔ taxonomy of non-essential and thus “suspended sectors”). Re-opening phase starting in may.
- **The second Covid-19 survey** (data collection between October 23 – November 13) **coincided with the second wave of the pandemic in Fall 2020 ➔ new restrictions on services** (since the end of October) **➔ We focus on industrial sectors only.**
- We drop a few firms which, according to updates of the ASIA Imprese register, ceased to be functioning before march 2020
- We drop also a few firms without sales in either 2018 or 2019
- We end up with a data set of more than 16,000 observations

Some descriptive statistics (1/2)

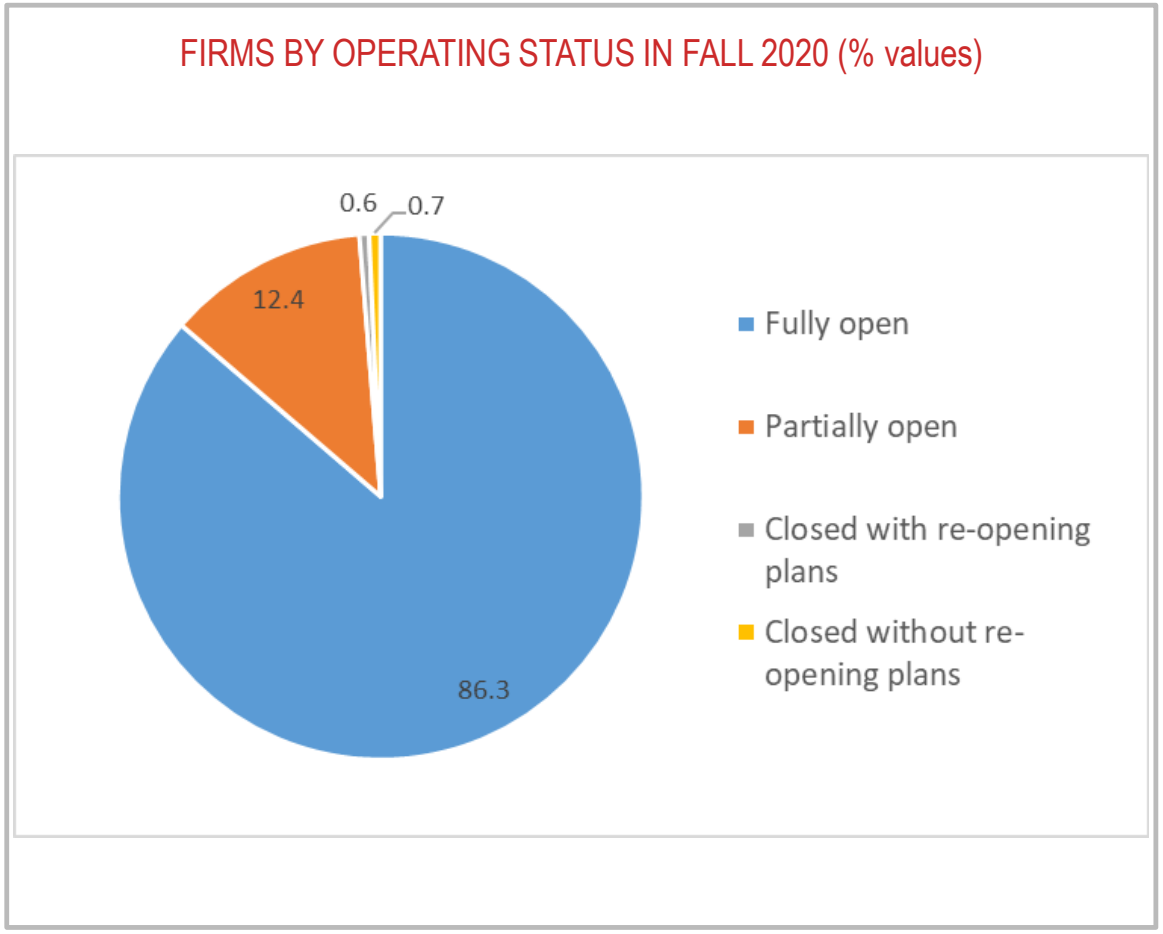
Most industrial firms were actually at work in Fall 2020. However, a small part of them were not.

➔ **Research question:** which factors discriminate between the two sets of firms ? (Differently stated: **what characterizes the minority of closed firms ?**)

Our answer: We provide some evidence that, once controlled for known relevant (and other possibly relevant) factors, this group of firms is characterized – **inter alia**-by **a significantly lower propensity to provide training**.

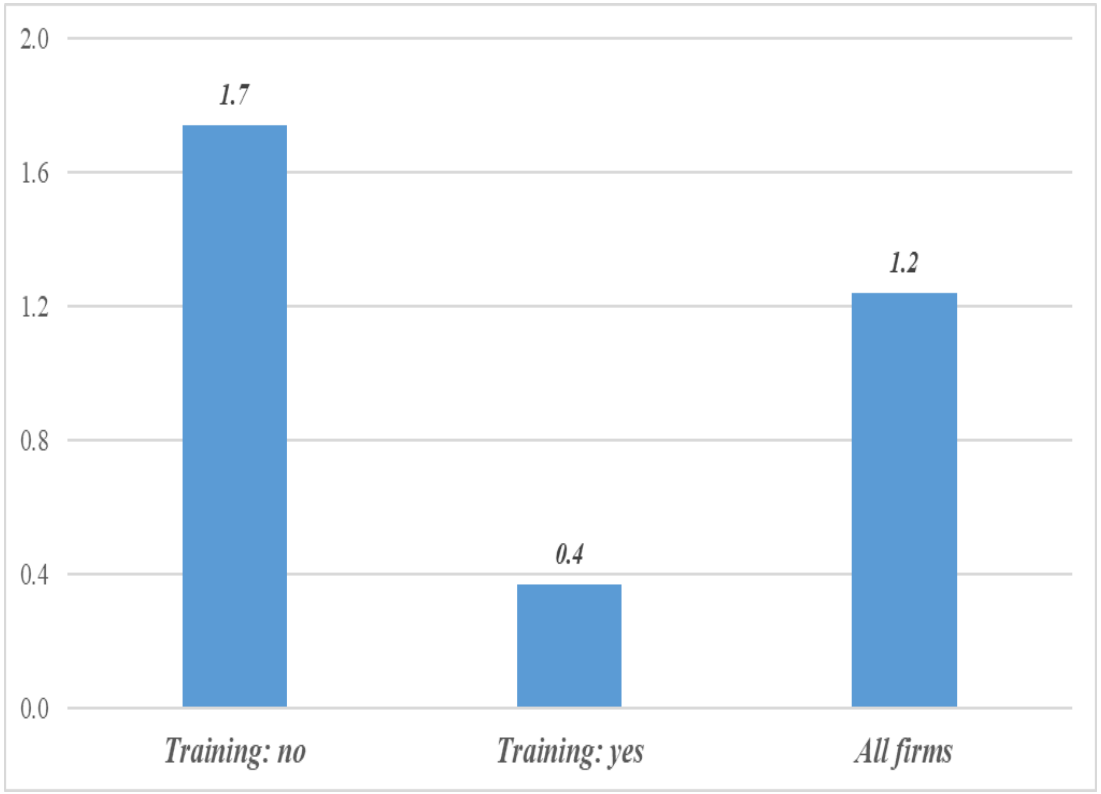
Next slide: a clue why training may matter (though we have to check for confounding effects).

Formally, we test the impact of training through logistic models.



Some descriptive statistics (2/2)

CLOSED FIRMS BY TRAINING PROVISION (%)



FIRM SIZE, OPERATING STATUS AND TRAINING PROVISION (%)

3 - 9	10 - 49	50 - 249	250+	***All firms***
		Firms by size class (%)		
42.5	36.2	16.1	5.2	100.0
		Closed firms by size class (%)		
2.2	0.7	0.4	0.1	1.2
		Firms providing training by size class (%)		
18.4	36.5	72.2	89.0	37.3

Estimators and empirical specification

- **Probit**: baseline estimator (usual presentation in terms of latent variables; Wooldridge, 2010)

$$Y_j^* = \boldsymbol{x_j}'\beta + \delta T_j + \varepsilon_j \qquad Y_j = 1[Y_j^* > 0] \qquad \Pr[Y_j = 1 | \boldsymbol{x}, T] = \phi(\boldsymbol{x_j}'\beta + \delta T_j)$$

where ***x*** denotes a **vector of variables affecting variation in *Y***

- **Robit**: «robust» probit (Liu, 2004), to deal with outliers (assumes Student-t distribution for errors)

- **Bivariate Probit** (**Biprobit**, Heckman 1978) to handle endogeneity due to possible omitted variables bias:

$$\begin{cases} T_j^* = \boldsymbol{x_j}'\alpha + \boldsymbol{z_j}'\gamma + \varepsilon_{1j} & T_j = 1[T_j^* > 0] \\ Y_j^* = \boldsymbol{x_j}'\beta + \delta T_j^* + \varepsilon_{2j} & Y_j = 1[Y_j^* > 0] \end{cases}$$

Han & Vytlacil (2017): restriction exclusions needed for global identification

where ***z*** denotes a **vector of variables affecting treatment** (but not outcome) and errors are supposed to be jointly normally distributed with zero mean and unitary variance.

- **Nearest-Neighbour Matching**

Explanatory variables in the outcome and training equations

- **Control variables (*x* vector)**

- Size: dummies for small (10-19), small-med. (20-49), med.-large (50+) firms; microfirms (3-9 empl.) are the reference class.

- Firm age

- Ex-ante performance: Labor productivity, Exporter status, High Financial Risk

- Ownership characteristics (Family, Artisan,Group)

- Digitalized/Innovating Firm (dummy)

- Education (share of graduate workers)

- Dummies for geographical macro-areas

- Sectoral effects: dummies for Nace2 (two dig.) & for «Suspended Sectors» (MISE-DM, march 25th 2020)

- **Instruments variables (*z* vector)**

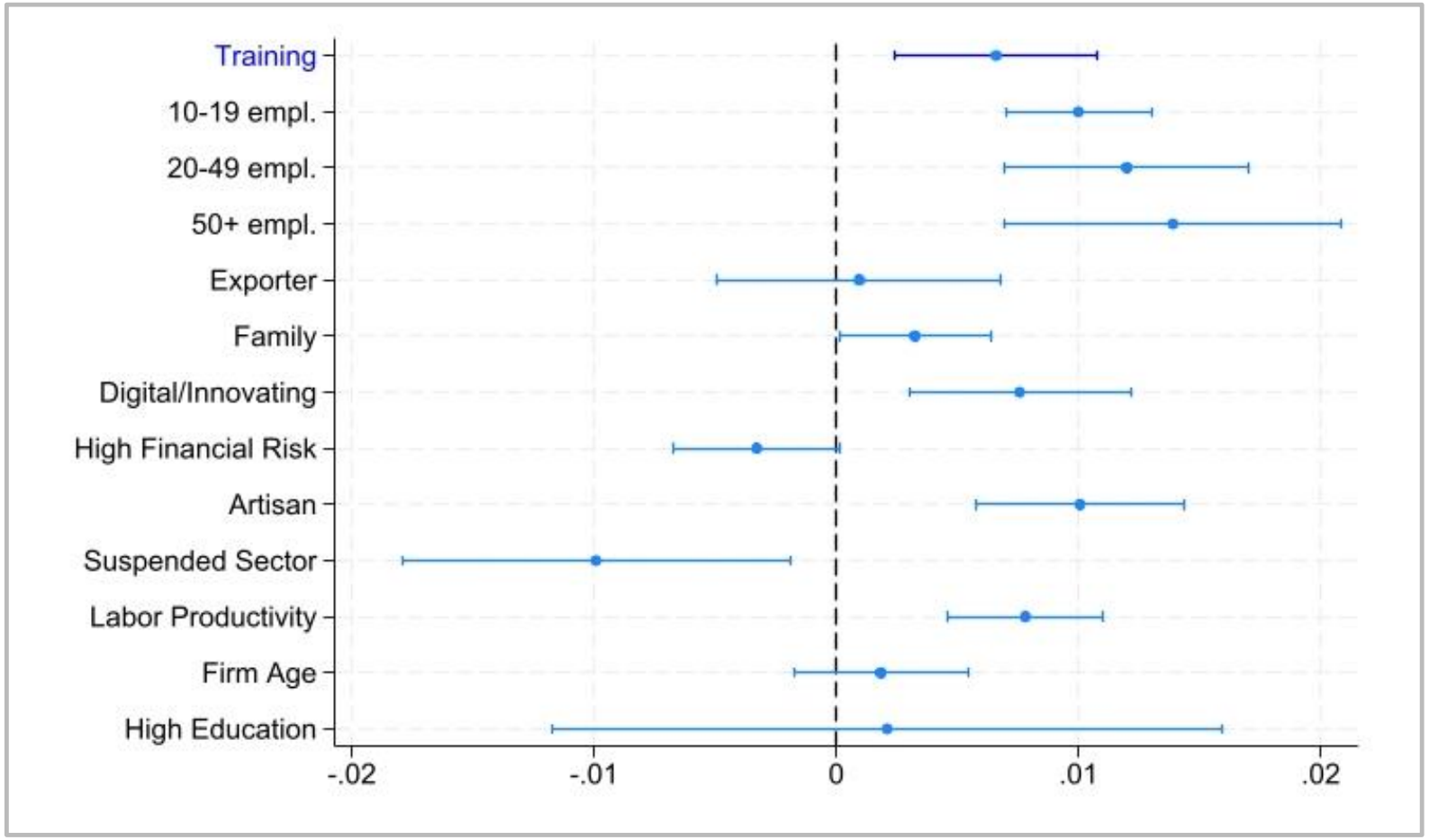
- Share of wage earners in the total number of employees («addetti»)

- Share of Apprenticees in the total number of employees

Rational: training is mostly directed to these categories of workers.

In the following, results generally presented in terms of «Average Marginal Effects» (AMEs)
In the case of discrete variables, AMEs may be computed for subgroups of observations. Also, they ma interpreted as «average tratment effects». i.e. the change in the conditional probability of success (Wooldridge, 2010).

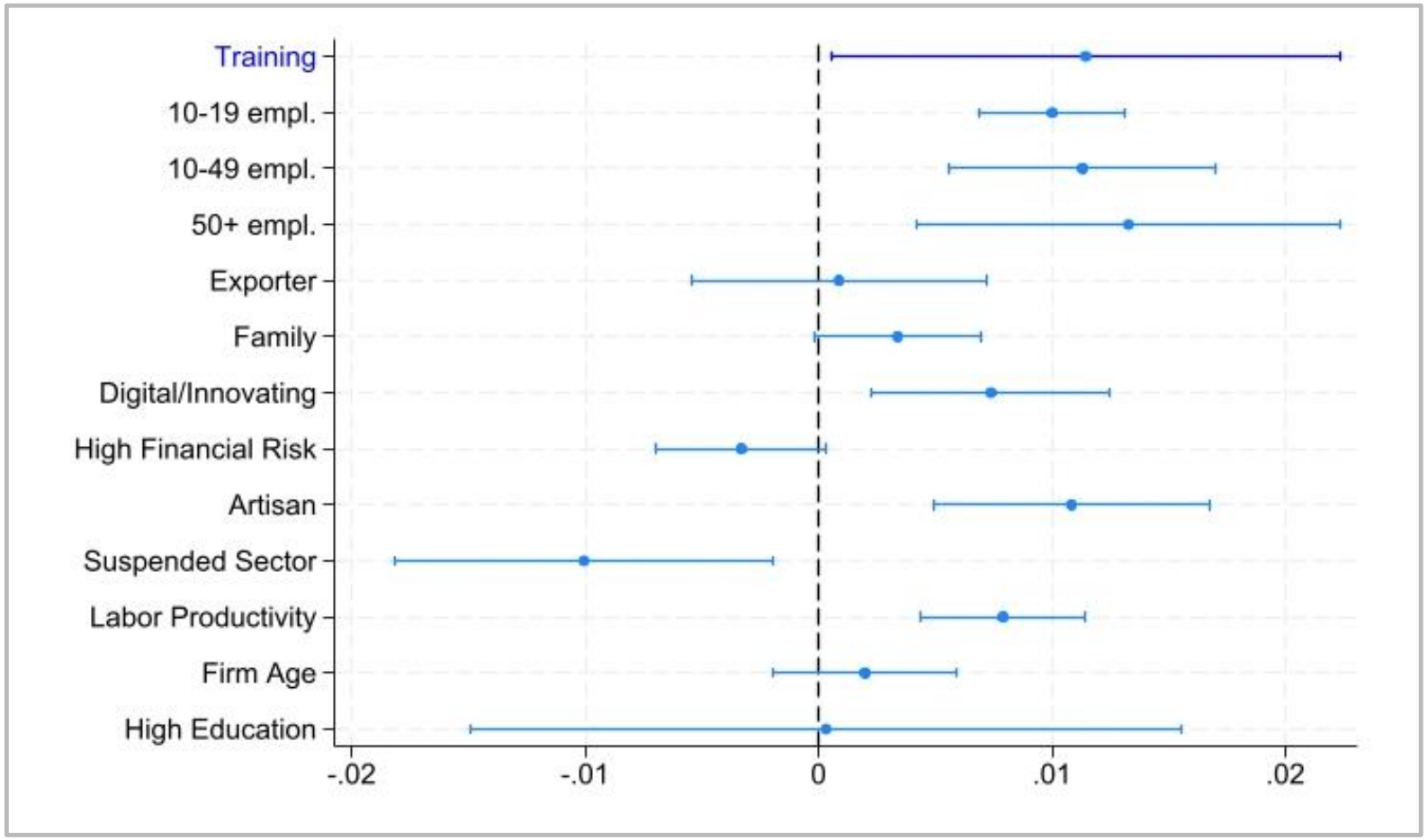
Probit results: Average Marginal Effects (AMEs)



AME of training significantly positive; it increase a firm's likelihood by around .7%. Results of most covariates in line with expectations: **higher probability of being open for larger, more productive, more innovating firms.** Family and artisan firms more resilient. **«Suspended» dummy significant**. **Education insignificant** (though significant in the subset of manufacturing firms).

Some evidence of heterogeneous effects and nonlinearities (see later)

Biprobit results: Average Marginal Effects (AMEs)



Biprobit results qualitatively similar to probit ones. AME of training again significantly positive and a bit larger than in probit estimation, >1% (though errors are a bit larger, as well). Alternative ways to address endogeneity lead to similar conclusions (see next slide).

Training equation (unreported): higher probability of *T*=1 when size is bigger, ex-ante performance is better and the share of graduates is higher.

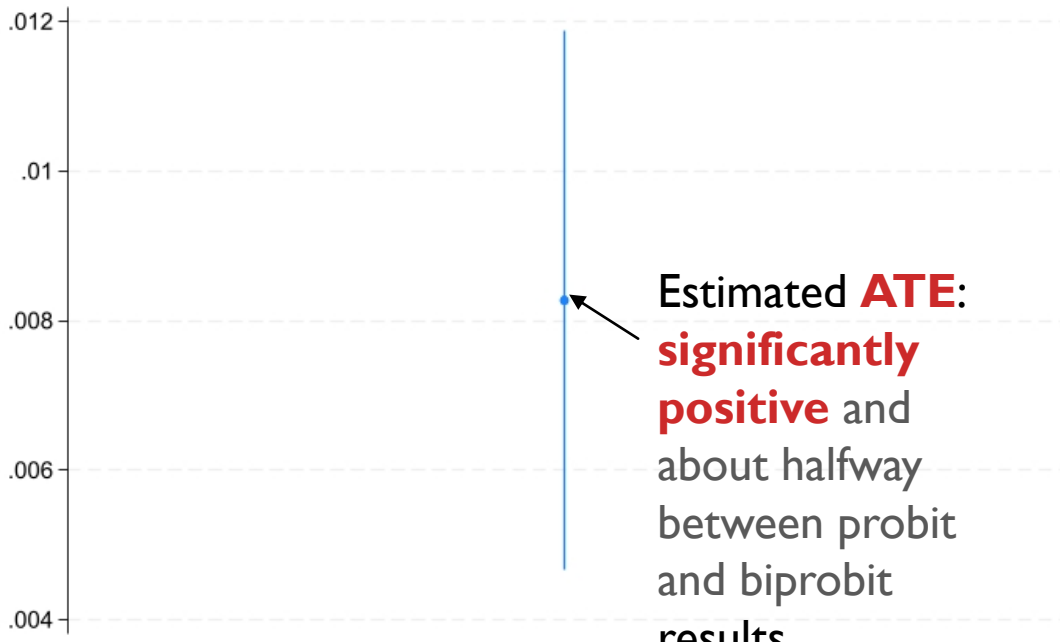
Results from a (nearest-neighbour) matching estimator

AVERAGE TRATMENT EFFECT

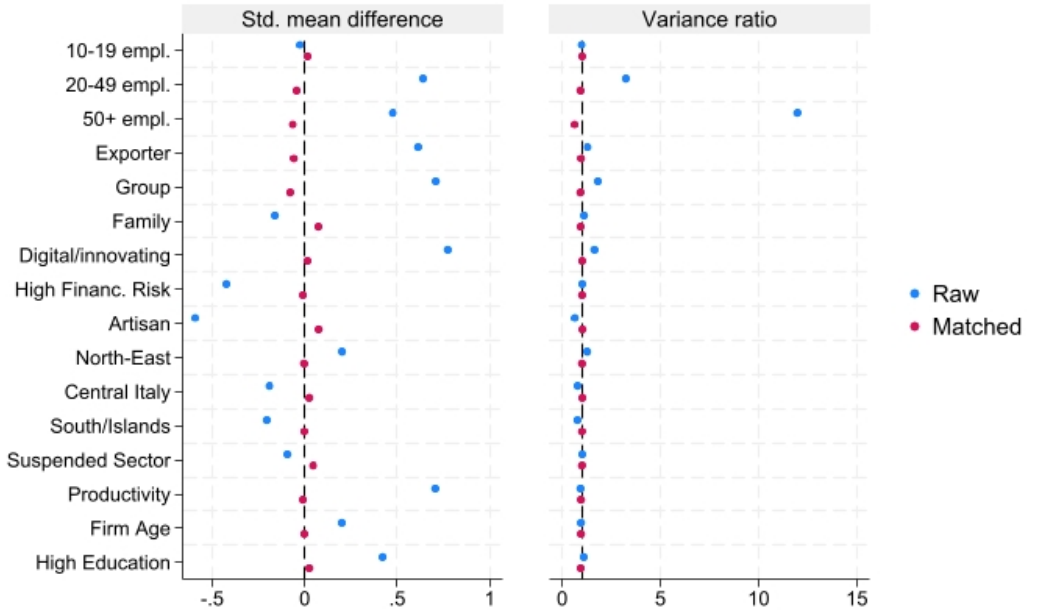
COMMON SUPPORT STATISTICS

Exact matching on Nace2

Adressing endogeneity bias without relying on exclusion restrictions)



Estimated **ATE**: **significantly positive** and about halfway between probit and biprobit results

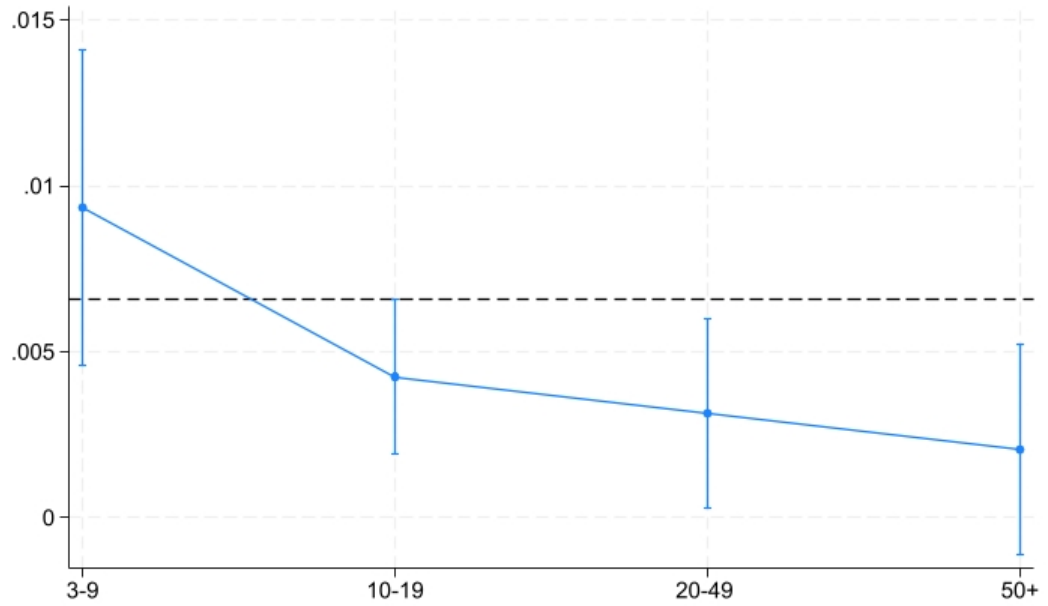


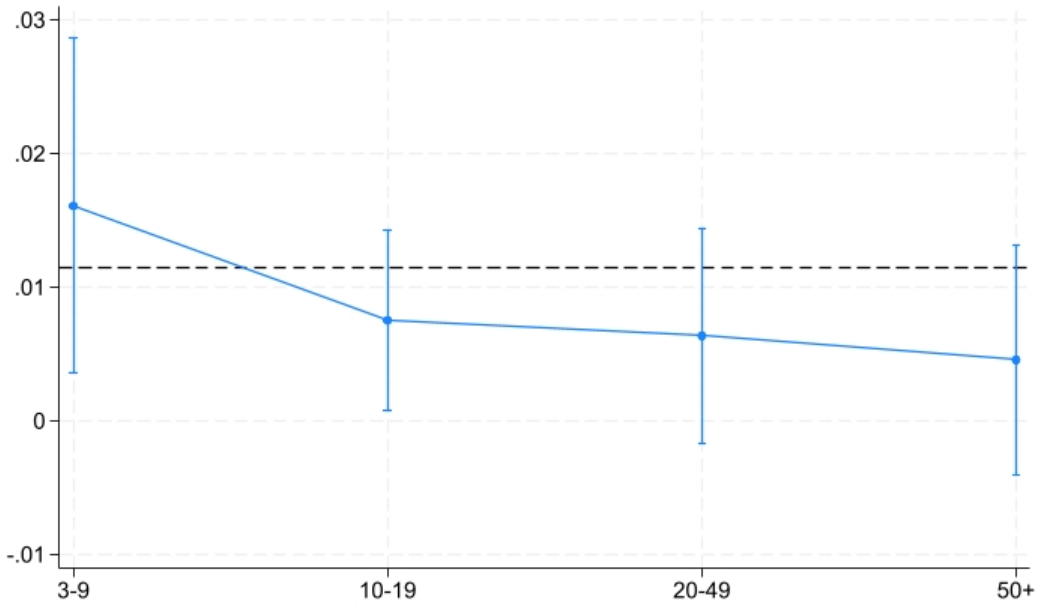
Heterogeneity and nonlinearities: ATEs of Training by size class

PROBIT

BIPROBIT

Some evidence that **marginal effects of training** are **significantly larger among smaller firms** (i.e. among producers which are less likely to train)





Heterogeneity and nonlinearities: adding interactions terms

Specifications with interactions

$$Y_j^* = \boldsymbol{x_j}'\beta + \delta T_j + \gamma(x_j * T_j) + \varepsilon_j$$

Not easy to implement with biprobit estimator (more instruments needed) ➔ tried alternative interactions at the time.

Results suggest that **the effect of Training was larger in «Suspended Sectors»**

No significant interactions of training with other covariates, including Education.

Estimator	Probit	Biprobit
	A) Coefficients	
Training	.0383881 (0.40)	.3643196 (1.49)
Suspended Sector	-.4617114*** (-2.82)	-.4371103*** (-2.62)
Training * Suspended Sector	.5118744** (2.47)	.5174506 ** (2.51)
Wald test for Training coeffs.	11.41 [.003]	13.49 [.001]
	B) Average Marginal Effects	
Training	.0074104*** (4.91)	.013557*** (3.08)
Suspended Sector	-.0105432** (-2.55)	-.0118195** (-2.66)

Does quantity matter ? Share of trained workers and resilience

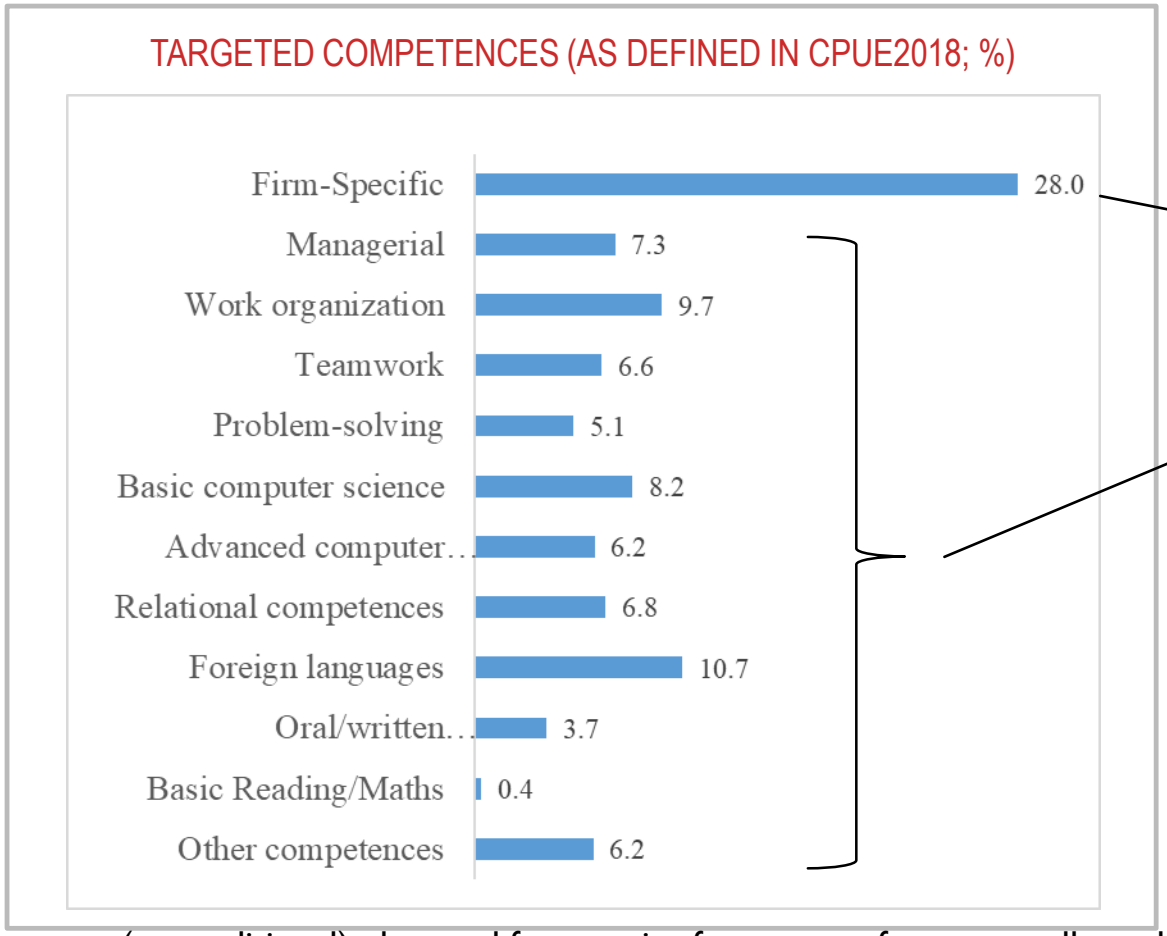
FIRM DISTRIBUTION BY THE SHARE OF TRAINED EMPLOYEES AND OPERATING STATUS

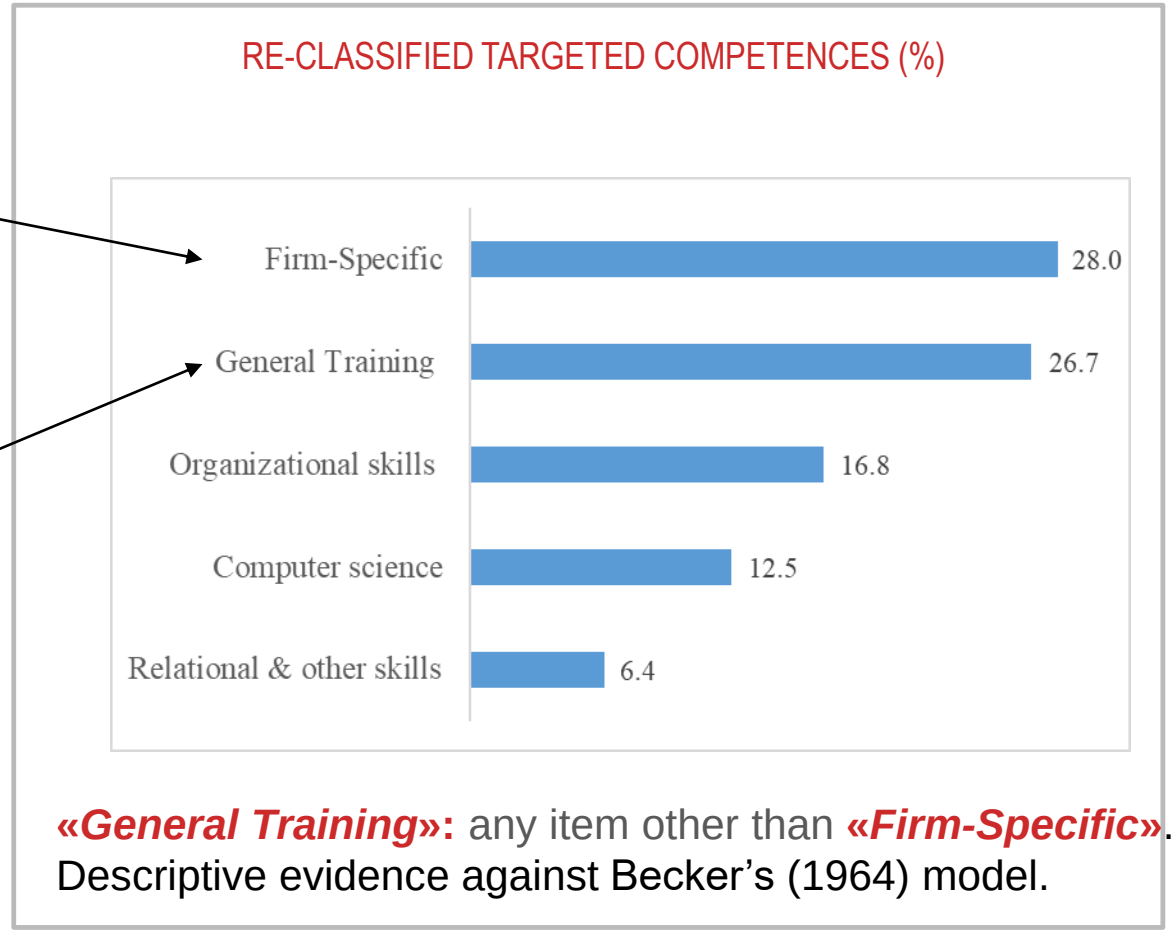
	Training 0 or less than 30% workers	Training from 30% to less than 50% workers	Training 50% workers and more
Total firms (%)	87.1	5.4	7.5
Closed Firms (%)	1.4	0.5	0.0

Descriptive statistics provide convincing evidence that **training a larger share of workers yields benefits.**

Firm-Specific, General Training and Resilience (1/3)

Question from CPUE2018: «**Which competences were targeted by training** ?»



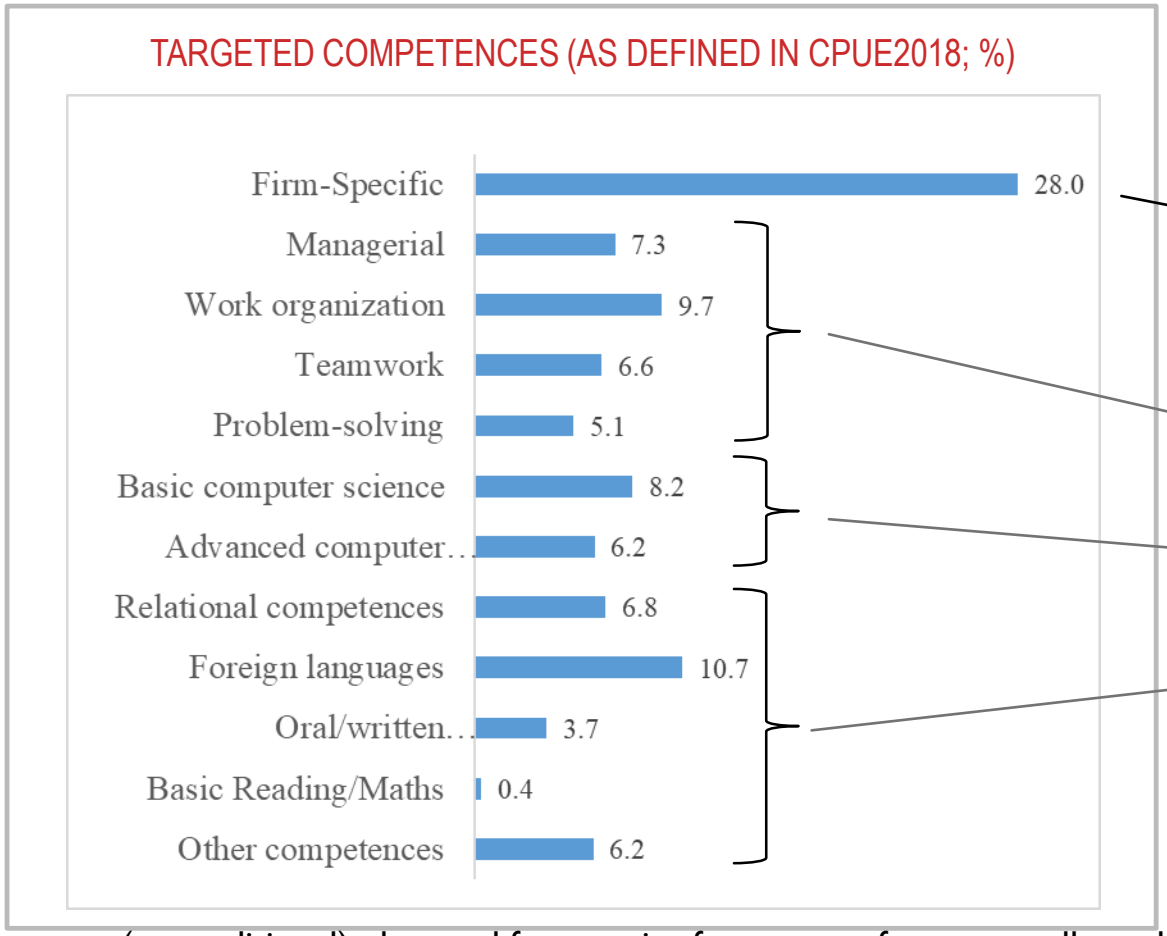


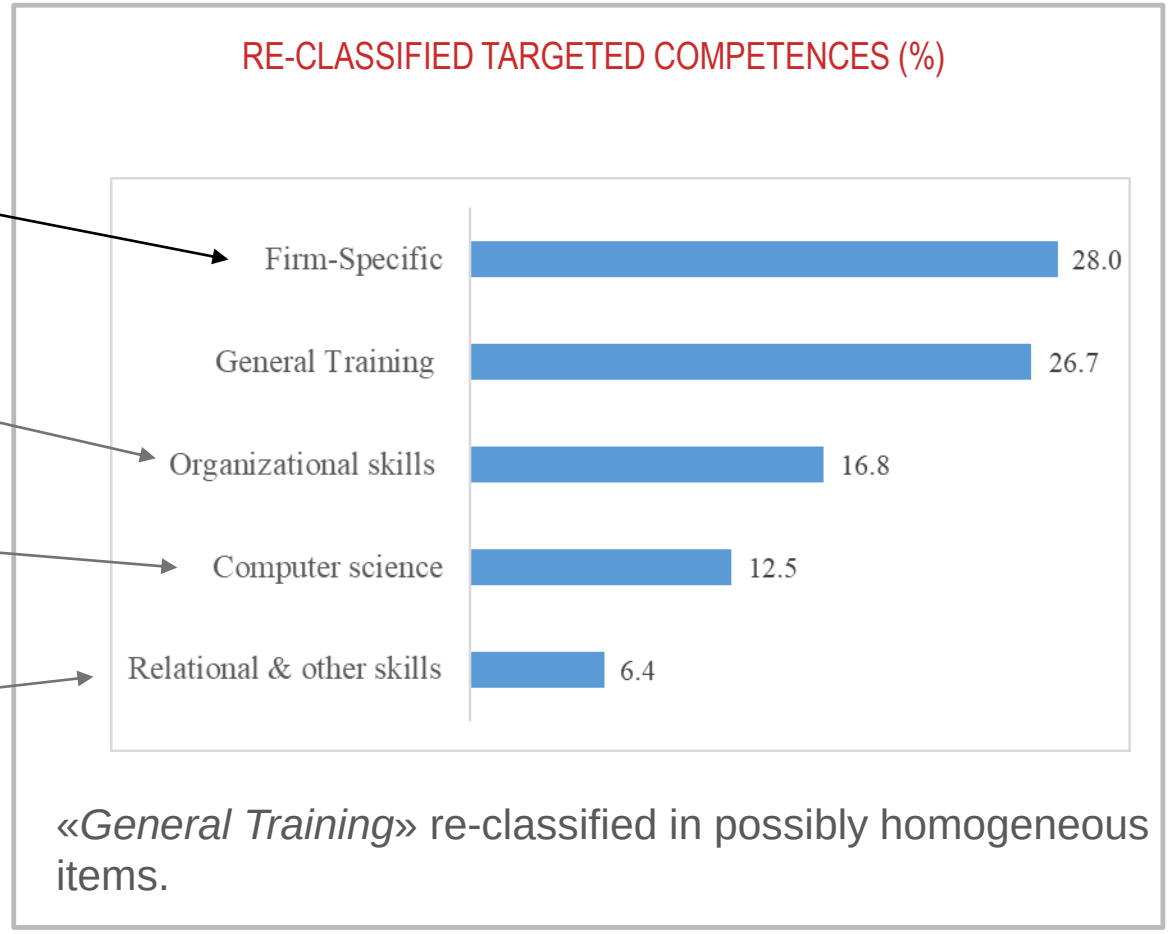
«General Training»*: any item other than *«Firm-Specific».
Descriptive evidence against Becker's (1964) model.

Values are (unconditional) observed frequencies from a set of non-mutually exclusive options

Firm-Specific, General Training and Resilience (2/3)

Question from CPUE2018: «**Which competences were targeted by training** ?»





«*General Training*» re-classified in possibly homogeneous items.

Values are (unconditional) observed frequencies from a set of non-mutually exclusive options

Firm-Specific, General Training and Resilience (3/3)

Re-classification provide us with **new binary variables measuring the provision of different forms of training** ➔ Alternative specifications to disentangle their impact upon the outcome variable.

We present only probit results.

Estimates suggest that **both «Firm-specific» and «General Training» were relevant** in building resilience abilities.

But which kind of «General Training» skills ? Evidence points out to a significant role played by broadly defined **«Managerial/Organizational» competences as well**.

Results seem robust to sample composition.

AVERAGE MARGINAL EFFECTS FROM PROBIT ESTIMATION

Regr. n.	(1)	(2)	(3)	(4)
Sample	*All units*	*All units*	*Dropping units providing exclusively firm-specific training*	*Dropping all units providing firm-specific training*
Specific Training	.0098*** (5.19)	.0091*** (5.70)	.00737** (2.15)	
General Training	.0087*** (3.15)			
Organizational skills		.00528* (1.69)	.00586* (1.75)	.00804* (1.77)
Computer Science		-.00016 (-0.03)	-.0001 (-0.02)	-.00094 (-0.10)
Relational & other skills		.00374 (0.73)	.004246 (0.77)	.00557 (0.73)

Summary and Conclusions

- By merging various Istat datasets, **the paper analyzes how a wide set of characteristics influenced Italian industrial firms in the aftermath of the first wave of Covid-19 pandemic**. Special focus on the role played by training. **Resilience is measured in terms of a binary "open/closed" operating status variable in Fall 2020**.

- Results from different estimators suggest that the **ex-ante provision of training is indeed associated to a higher degree of resilience** by firms. Larger effects of training for smaller firms and those working in «suspended» sectors. Both firm-specific and general training yielded benefits.

- Results concerning other explanatory variables in line with previous evidence (size matters, digitalization and propensity to innovation fostered resilience, cleansing effects were at work).

- Results of interest for policymakers (18% of "not-training" firms: costs too high; 21% say: time constraints). Possible sub-optimal levels of training due to a wedge between firm and social returns ? ➔ **More research on the role played by training seems desirable**.

References (1/2)

- Bartoloni E., Arrighetti A. Landini F. (2021), "Recession and firm survival: is selection based on cleansing or skill accumulation?," Small Business Economics, vol. 57(4), 1893-1914.
- Collier W., Green F., Kim Y., Peirson J., (2011), "Education, Training and Economic Performance: Evidence from Establishment Survival Data," Journal of Labor Research, 32(4), 336-361.
- Han S., Vytlacil E.J. (2017), “Identification in a generalization of bivariate probit models with dummy endogenous regressors”, Journal of Econometrics, 199, 63, 63-73.
- Heckman J. (1978), “Dummy endogenous variables in a simultaneous equations system”, Econometrica 46, 931-959.
- Heckman, James J. & Lance Lochner & Christopher Taber (1998) ‘Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents’,
- Lengnick-Hall, C.A., Beck, T.E., and Lengnick-Hall, M.L. (2011), “Developing a capacity for organizational resilience through strategic human resource management,”, Human Resource Management Review. Vol. 21, N. 3, 243-255.
- Liu, C. H., (2004). Robit Regression: A Simple Robust Alternative to Logistic and Probit Regression. In “Bayesian Modeling and Causal Inference from Incomplete–Data Perspectives: An Essential Journey with Donald Rubin’s Statistical Family”, ed. A. Gelman and X.-L. Meng, chap. 21. John Wiley & Sons, Ltd.

References (2/2)

- Martinelli E., Sarti E., Tagliazucchi G. (2024), “Assessing long-term performance in manufacturing Companies hit by a natural disaster: the role of organizational resilience and human capital”, in “Sustainable and Resilient Global Practices: Advances in Responsiveness and Adaptation”, ed. Torben Juul Andersen, 37–54; Emerald Publishing Limited.
- Martins, Pedro S. (2022) : The Economic Implications of Training for Firm Performance, GLO Discussion Paper, No. 1046, Global Labor Organization (GLO), Essen.
- Mincer J. (1962), “On-the-job training: Costs, returns, and some implications”, The Journal of Political Economy, 70(5), Part 2, 50-79.
- Muzi S., Jolevski F., Ueda K, Viganola D. (2023), “Productivity and firm exit during the COVID-19 crisis: cross-country evidence”, Small Business Economics, vol. 60, 1719-1760.
- Teece D.J. (2017), “Towards a capability theory of (innovating) firms: implications for management and policy”, Cambridge Journal of Economics, 41(3), 693-720.
- Wooldridge J.M. (2010), “Econometrics analysis of cross section and panel data”, MIT Press, New York.

grazie

ANDREA MARINO | anmarino@istat.it

Istat | Istituto Nazionale di Statistica