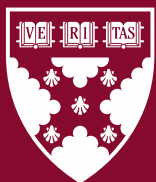


Working Paper 26-041

Unwilling to Reskill? Experimental Evidence from Real-World Jobseekers

Alexia Delfino
Andrea Garnero
Sergio Infrerra
Marco Leonardi
Raffaella Sadun



**Harvard
Business
School**

Unwilling to Reskill? Experimental Evidence from Real-World Jobseekers

Alexia Delfino

Bocconi University

Andrea Garnero

OECD

Sergio Infrerra

Queen Mary University of London.

Marco Leonardi

University of Milan.

Raffaella Sadun

Harvard Business School

Working Paper 26-041

Copyright © 2025, 2026 by Alexia Delfino, Andrea Garnero, Sergio Infrerra, Marco Leonardi, and Raffaella Sadun.

Working papers are in draft form. This working paper is distributed for purposes of comment and discussion only. It may not be reproduced without permission of the copyright holder. Copies of working papers are available from the author.

Funding for this research was provided in part by Harvard Business School, the PNRR - MUSA 6 project, CEPREMAP, and the Economic Social Science Research Council, grant number ES/Y001850/1.

Unwilling to Reskill?

Experimental Evidence from Real-World Jobseekers^{*}

Alexia Delfino, Andrea Garnero, Sergio Infrerra

Marco Leonardi, Raffaella Sadun

February 13, 2026

Abstract

We study barriers preventing jobseekers from pursuing reskilling in high-demand occupations. Using a discrete choice experiment, we quantify the demand for reskilling among Italian jobseekers in two white-collar high-demand occupations—information technology assistant and construction technician—and identify its main determinants. Willingness to pay estimates show that participants are willing to pay to reskill into IT, but would require compensation to reskill into construction. Beliefs about monetary returns and social status help explain differences in reskilling demand, but perceived identity fit in the target occupation emerges as the most important individual-level factor shaping reskilling decisions. A light-touch randomized information intervention providing data on occupational returns significantly increases both stated interest in reskilling and actual engagement in real-world training.

^{*}We thank seminar participants at Bank of Italy, Berkeley, Bocconi, CREST, Glasgow, Naples Federico II, OECD, Tilburg, Collegio Carlo Alberto and Queen Mary University of London. Marco Visentin and Clara Morelli provided superb research assistance. We would like to thank AFOL Metropolitana and its leadership for their partnership on this project, and in particular Simone Cerlini, Tommaso Di Rino, Mario Giaccone, Antonio Tursi and Maria Minervini. We thank Francesco Armillei, Sam Altmann, Elie Ofek, Miguel Espinosa and Antonella Trigari and Soumitra Shukla for advice. We gratefully acknowledge financial support by the PNRR - MUSA 6 project and by CEPREMAP. Sergio Infrerra gratefully acknowledges the support from the Economic Social Science Research Council, grant number ES/Y001850/1. The study was pre-registered in the AEA-RCT registry with ID: AEARCTR-0011866. Delfino: Bocconi University, LEAP, IGIER. Garnero: OECD and IZA. Infrerra: Queen Mary University of London. Leonardi: University of Milan. Sadun: Harvard University, NBER and CEPR.

1 Introduction

Technological change, globalization, and the green and digital transitions are reshaping the demand for skills (Acemoglu and Restrepo, 2018; Karabarbounis and Neiman, 2014; Autor et al., 2013). Policy makers increasingly view reskilling—training that helps workers pivot into new, high-demand occupations—as a key response (OECD, 2023; World Economic Forum, 2020). Recent industrial policies, from U.S. semiconductor initiatives to EU green-transition plans, hinge on large-scale reskilling to redeploy labor toward strategic sectors. Rigorous evaluations show that well-designed training and sectoral employment programs that reskill workers into high opportunity occupations raise earnings and employment (Card et al., 2018; Goller et al., 2021; Lechner and Wunsch, 2009; Leung and Pei, 2023; Katz et al., 2022; Humlum et al., 2025; Humlum and Plato, 2025). Yet, the average take-up of adult training opportunities—even when highly subsidized—remains stubbornly low (OECD, 2023). Understanding interest in reskilling among jobseekers is critical to assess the feasibility and costs needed to retrain a large number of workers into in-demand occupations.

In this paper, we provide the first quantitative characterization of the appeal of reskilling among jobseekers. Our analysis focuses on Italy—a country marked by low adult numeracy and literacy, a large population not in education, employment or training (“NEET”) and persistent skill mismatches (OECD, 2017). Despite recent investments in active labor market policies, participation in training remains limited (Fialho et al., 2019). We partnered with one of the country’s largest public employment-service networks to implement a survey experiment with 1,100 unemployed jobseekers who were actively navigating real-world decisions about training and potential occupational change. We use two complementary approaches to study jobseekers’ demand for reskilling and identify its main barriers. First, we collect survey measures of skills, expectations, and perceived identity fit—whether a new occupation feels compatible with a person’s sense of who they are—and examine how these factors shape reskilling choices in a discrete choice experiment (DCE), where participants select between hypothetical courses. Second, we embed randomized interventions within the survey to test whether reskilling interest and real-world take-up can be increased.

Results from the DCE and the survey show that perceived identity fit is the main individual-level barrier to reskilling, beyond perceived skill adjacencies and wage expectations. Among course features, jobseekers place the highest value on post-training job-finding prospects. The randomized information intervention shows that information on wages and job opportunities matters, but its effects are heterogeneous and concentrated among individuals with relatively high identity fit—consistent with identity

acting as a precondition for responsiveness to other policies. Together, these findings imply that effective reskilling policy requires two distinct levers: targeting—by matching workers to occupations that fit their identity—and information—by clearly signaling program quality and employment prospects. Simply expanding training supply or offering uniform subsidies is therefore unlikely to generate large participation.

We start from the premise that reskilling differs fundamentally from generic training because it equips individuals with the skills required for a *new* occupation rather than the one in which they previously worked. Choosing to reskill therefore entails an implicit occupational switch rather than a marginal skill upgrade, making the decision more complex than a standard human capital investment. Beyond comparing expected training costs and returns, individuals must assess whether they can succeed in a new occupational path. Learning costs tend to rise when the skills required in the new occupation are farther from what workers already know. Switching costs may also include non-pecuniary factors such as concerns about identity fit, social status, and work environment ([Akerlof and Kranton, 2000](#)). Alongside these cost-side considerations, limited prior exposure to the new occupation creates uncertainty about its wage and demand prospects, with workers holding beliefs that are often noisy or systematically biased ([Mueller and Spinnewijn, 2023](#); [Chakravorty et al., 2024](#); [Bhatiya et al., 2024](#)). Together, these frictions imply that, even when reskilling promises higher wages, many jobseekers may view the transition as too costly or uncertain—making reskilling choices more complex and context-dependent than generic training investments.

To formalize this intuition, the paper first outlines a simple Roy-style framework of occupational choice. Individuals choose between two training programs: a generic course that maintains their current occupational path, and a reskilling course that enables a switch to a new occupation. When deciding which program to attend, agents balance the potential benefits of an increased wage with learning and identity costs (i.e. the utility cost of entering an occupation which is a worse fit with one’s identity), plus an idiosyncratic taste shock. The framework provides guidance for the empirical analysis by expressing willingness to pay (WTP) for reskilling as a function of these components, and clarifying how heterogeneity in information, learning, and identity frictions shapes observed choices.

To empirically link the framework to observed behavior, we fielded a survey that combines a discrete choice experiment (DCE) and detailed measures of the model’s core components, including expected returns, perceived learning costs, and perceived identity fit with the occupation targeted by reskilling. Each respondent was randomly assigned to focus on a single target occupation—either information technology assistant (IT) or construction technician—and all survey questions (e.g., expected wages)

referred to that occupation. The two occupations were selected because they are white-collar, office-based technical roles (e.g., “construction technician” is a design coordination role rather than on-site labor) that do not require a college degree, offer high entry wages, and can be accessed through short, modular training programs. By randomly assigning the target occupation across respondents, we can study how occupation-specific characteristics shape stated reskilling choices across demographic groups with different occupational preferences and expectations.

In the DCE, respondents make repeated choices between a generic training option and a reskilling course leading to their assigned occupation. Course options vary exogenously in price and features such as duration and post-training job-placement probability. This design allows us to estimate individuals’ willingness to pay (WTP) for reskilling relative to generic training—interpreted as the cost or premium of switching occupations—while holding training supply conditions and course attributes constant. By combining experimental variation in course features with rich survey measures, we quantify how expected returns, learning costs, and identity-related factors shape reskilling preferences and predicted participation. Overall, this approach provides a cleaner and more policy-relevant measure of reskilling demand than what can be inferred from observational data alone.

We document three key findings on jobseekers’ willingness to reskill using descriptive evidence from the survey and the DCE. We do so by examining the raw frequency with which respondents choose reskilling versus generic training across scenarios and relating these choices to observable characteristics. First, on average, respondents choose reskilling and generic training with roughly equal frequency, indicating limited willingness to switch occupations despite higher expected returns in the reskilling options on average. Second, reskilling choices vary sharply across target occupations: respondents choose reskilling more often when the target occupation is in information technology (IT) than when it is in construction, consistent with differences in perceived switching costs and returns across fields. Third, variation in reskilling choices is strongly associated with perceived identity fit, which emerges as the dominant barrier to reskilling, outweighing monetary considerations such as expected wages or perceived learning effort.¹ Among demographic characteristics, older participants are less likely to choose reskilling in these scenarios ([Ben-Porath, 1967](#)).

To quantify the trade-offs underlying these patterns, we use data from the DCE to estimate a logit model of course choice, which allows us to compute a willingness to pay for reskilling, benchmark it against the WTP for other course features, and examine how it varies with expected returns, learning

¹Perceived identity fit is measured through a survey item asking whether respondents feel that the target occupation aligns with their identity and self-concept.

costs, and identity-related factors. On average, respondents are willing to pay about €3.5 per training hour to reskill into IT, but would require a €5.3 per-hour subsidy to train for construction—despite comparable course characteristics (by design), and controlling for beliefs and demographics. Among respondents with below-median perceived identity fit in construction, the required subsidy reaches €10 per hour, whereas those with above-median fit would be willing to pay €3.8 per hour. Among training features, program quality plays a central role. This means that, even if reskilling targets high-demand occupations, jobseekers seek reassurance that the specific program they choose will translate into actual employment opportunities. A 10-percentage-point increase in job-placement probability is valued at roughly €160 for a 100-hour course—slightly more than the average course fee in our scenarios.

Using the structural WTP equation from our framework, we simulate how reskilling participation—measured by the predicted share choosing reskilling in the logit model—responds to changes in expected returns, learning costs, and identity-related costs, holding course features and individual characteristics constant. The simulations show that improving the perceived identity fit with the target occupation or improving course quality lead to large increases in participation, whereas modifying wage gains or learning costs has comparatively minor effects. The limited role of expected returns and learning costs in explaining the simulated reskilling take-up aligns with our survey evidence, indicating that many jobseekers misperceive both the rewards and the effort required to switch occupations. About 75% of our respondents underestimate wages in the target occupations, nearly 40% underestimate labor demand, and around 22% report having fewer relevant skills than their past experience would imply. These patterns motivate us to test whether providing accurate information or reducing perceived switching costs can increase interest in reskilling.

We embedded two randomized light-touch treatments into the survey. One-third of respondents received concise information on wages and vacancies in their assigned occupation, aimed at correcting potential information gaps (and, presumably, raising expected returns of reskilling). Another third of the sample received a “growth-mindset” vignette, aimed at lowering perceived switching costs, related to either learning or identity fit. The remaining third served as a control group. We examine the effect of our treatments on both stated intentions and willingness to pay (WTP) to reskill in the survey, as well as on real-life training and job outcomes collected in external administrative data.

Results from our randomized interventions show that providing accurate information on wages and job openings raises reskilling demand, but selectively. Information boosts reskilling intentions—as stated in the DCE—by 11% over the control mean ($p < 0.05$). The gains are concentrated among participants who initially underestimated wages in the treatment occupation—suggesting that the inter-

vention’s effect reflects genuine belief updating rather than social desirability. However, the information treatment is effective primarily among individuals who already show some interest in the targeted occupation, while roughly 25% of respondents—those with a very low WTP to reskill—remain largely unresponsive. The impact of information is also concentrated among people whose identity-fit costs are not too high, suggesting that perceived identity fit can also shape the effectiveness of other policies, beyond its direct effect on reskilling intentions. The mindset treatment produces smaller and statistically insignificant effects, indicating that perceived learning and identity barriers are harder to shift.

Importantly, the information treatment also has real-world effects: in the IT arm, it significantly increases both reskilling enrollment and subsequent employment in IT-related occupations. This result provides external validation of the experimental effects and highlights the potential of information to shift behavior. Strikingly, none of the participants engaged in training within the construction sector during the study period, consistent with their lower willingness to reskill into this sector, and despite expecting higher wages in construction than in IT. Taken together, these findings have direct implications for the design and delivery of reskilling policies and public employment services: providing clear information on wages and job prospects, and helping jobseekers identify occupations that feel like a good personal fit, can meaningfully increase engagement with reskilling.

Our paper contributes to three literatures. First, it relates to the growing body of evidence on the role of training in reducing unemployment and labor market frictions ([Crépon and Van Den Berg, 2016](#); [Jones et al., 2012](#); [Manuti et al., 2015](#)). Work on the demand for training and reskilling is scant. Notable exceptions are the paper by [Bassanini and Ok \(2004\)](#), who explore how the demand and supply of training can explain take-up across OECD countries, [Lergetporer et al. \(2023\)](#), who show that information on occupations’ automatability increases respondents’ concerns about their professional future and willingness to participate in further training, and [Brosch et al. \(2025\)](#), who show that beliefs about earnings and non-pecuniary outcomes explain training intentions within firms. Evidence from successful sectoral training models shows that improved labor market outcomes depend not only on program design but also on enrolling motivated individuals who are a good fit for the target occupation ([Katz et al., 2022](#); [Schochet, 2001](#)).² Our findings help explain why: the demand for reskilling varies widely across individuals, and is strongly influenced by hard-to-observe factors like perceived identity fit and expectations. This highlights the importance of targeting—but also exposes a key challenge for scaling. Our results suggest that improving training take-up at scale requires not just expanding access,

²In Italy, [Bazzoli et al. \(2026\)](#) show positive effects of long (400 hours) reskilling programs coupled with work experience. Lessons from developing countries also suggest that training programs can be successful when targeted to skills in need in high-demand occupations ([Attanasio et al., 2011](#); [Alfonsi et al., 2020](#)). Other papers focus on documenting the positive impact of alternative active labor market policies and incentives for jobseekers’ reemployment ([Zanella and Salomone, 2025](#); [Kluve, 2010](#)).

but actively addressing information gaps, and dramatically improving targeting.

Our results also contribute to the growing literature on identity and labor market behavior. Prior work has shown that identity concerns shape labor supply and can contribute to the persistence of occupational segregation (e.g., [Akerlof and Kranton, 2000, 2002](#); [Shayo, 2020](#); [Cassan et al., 2021](#); [Oh, 2023](#); [Delfino, 2024](#)). By quantifying identity-related switching costs and comparing them to monetary returns, we provide direct evidence that perceived identity fit is a central determinant of reskilling decisions. This insight enriches standard interpretations of occupational mobility and retraining decisions—typically framed around wage or skill-adjustment frictions—by showing that psychological barriers related to professional identity represent a distinct and substantial component of occupational switching costs.

Third, we contribute to the literature on the impact of information provision on educational and occupational choices. Prior RCTs have examined how information influences higher education decisions ([Hoxby et al.](#); [Goux et al., 2014](#); [Kerr et al., 2020](#); [Bächli et al., 2025](#)) and job search behavior among the unemployed ([Altmann et al., 2018](#); [Belot et al., 2019](#); [Behaghel et al., 2022](#); [Belot et al., 2024](#)). We extend this work by focusing on reskilling intentions—a forward-looking margin of labor market adjustment that has received less attention. We show that providing clear, occupation-specific labor market information can shift both intentions and actual training take-up. Our findings also highlight who responds to such interventions, offering insights for more targeted and cost-effective policy design.

The remainder of the paper is organized as follows. Section 2 describes the institutional context. Section 3 presents a simple theoretical framework to guide our empirical analysis. Section 4 explains our survey design and describes the sample. Section 5 presents three main facts about respondents’ reskilling intentions and Section 6 uses a discrete choice model to quantify the WTP for reskilling. Section 7 asks whether the demand for reskilling can be reshaped through light-touch interventions. Section 8 concludes.

2 Institutional Context

Skill shortages are pervasive in Italy. According to the PIAAC Survey of Adult Skills, 35% of adults aged 16–65 have low literacy or numeracy proficiency ([OECD, 2024](#)). Skill shortages are especially severe in high-demand sectors such as IT and STEM. As a result, Italy has one of the highest shares of underqualified workers in the OECD and the second-highest share of NEETs in the EU ([Garda, 2017](#); [Eurostat, 2022](#)).

Despite these gaps, adult training participation remains very low: only 7% of low-skilled adults were trained in 2023, compared to an 18% OECD average (PIAAC 2023). In addition, access to adult learning is lower for the inactive than for the employed: 8% of inactive adults participated in some form of adult learning in 2023, compared to 20% of the unemployed and 31% of the employed (OECD, 2025). Unlike other countries that have managed to increase learning among the low-skilled or unemployed, no notable changes were recorded between 2013 and 2023 (OECD, 2025). Even free courses designed specifically for unemployed jobseekers often struggle to attract participants, according to anecdotes by our field partners in Italy. Recent reforms have aimed to reverse this trend, notably through the National Recovery and Resilience Plan, which earmarked €4.4 billion for the GOL program—a large-scale package of active labor market policies. Yet more than two years into the program, only 10% of the 2 million registered jobseekers had begun training (ANPAL, 2024).

Training governance remains fragmented across multiple actors and levels of government.³ Moreover, the absence of systems of quality assurance leads to offerings often misaligned with local labor demand. Employment services, constrained by limited staff and resources, struggle to guide jobseekers effectively. Nevertheless, evidence from some virtuous regional programs suggests that well-targeted training aligned with industry needs can improve employment outcomes (Pastore and Pompili, 2022; IRES, 2022; OECD, 2017).⁴

The main open question concerns the demand side: why many adults, especially when inactive or unemployed, refrain from participating in available programs, and how workers' preferences and perceptions shape reskilling decisions, even when opportunities are well designed and subsidized. Beyond time, costs, and family constraints commonly cited as barriers (OECD, 2021), reskilling choices may also hinge on how individuals perceive new occupations—their expected returns, social status, and fit with personal identity. Our study examines these determinants directly, linking them to revealed training preferences and behavior in a real labor market context.

3 Reskilling: A Simple Conceptual Framework

We outline a simple Roy-style model (Roy, 1951) in which reskilling is a gateway to switching away from an individual's prior occupation into a new one. Agents compare expected returns in the destination

³The State defines education principles; regions regulate vocational training; and a mix of public centers, private providers, and sectoral funds deliver courses with limited coordination (OECD, 2019).

⁴Regional evidence shows that aligning training with local labor demand improves outcomes. European Social Fund (ESF) programs in Bolzano raised employment by linking courses to industry needs (Pastore and Pompili, 2022), and vocational training in Piedmont increased participants' employment rates by 6.6 percentage points one year after completion (IRES, 2022). The OECD similarly highlights that public-private coordination enhances training effectiveness and labor market integration (OECD, 2017).

occupation against training features, individual-specific learning costs, and non-pecuniary (identity) costs associated with changing occupations. Generic courses, in contrast, entail only training costs, and do not imply transitioning between occupations.

A job-seeker i chooses whether to take up reskilling (r) and switch to occupation o or to take up a generic training program (g). Comparing the utility associated with each option $j \in \{r, g\}$, the job-seeker chooses the option that maximizes her total utility:

$$U(i, j, o) = \max_j \left[U(i, r, o) \mathbb{I}\{j = r\} + U(i, g) \mathbb{I}\{j = g\} \right] \quad (1)$$

The utility associated with reskilling is the sum of the expected conditional returns and costs associated with both training activities and the subsequent occupational transition:

$$U(i, r, o) = \underbrace{\mathbb{E}[w(i, r, o)|X_i]}_{\text{Expected returns}} - \underbrace{C(i, r, o)}_{\text{Learning costs}} - \underbrace{\kappa(i, r, o)}_{\text{Non-pecuniary switching penalty}} + \underbrace{\varepsilon(i, r, o)}_{\text{Taste shock}} \quad (2)$$

Learning costs are designed to include both a fixed component associated with training (e.g., price of the course, duration, delivery mode) and a variable cost that depends on individual skills endowments. We assume that costs take the following functional form: $C(i, j, o) = F(j) + \mathbb{I}[j = r]\gamma(i, o)$, where $F(j)$ measures the fixed costs associated with training features (e.g., hours of training) and $\mathbb{I}[j = r]\gamma(i, o)$ measures the variable individual-specific costs triggered when switching occupation.⁵ In addition to the standard variable cost of effort, we include an intangible component, the *non-pecuniary switching penalty* $\kappa(i, r, o)$, which represents non-monetary costs associated with switching occupation (e.g., changes in social status or perceived identity fit). The utility features also an individual taste shock $\varepsilon_i(r, o)$, that we assume is drawn from a Gumbel distribution.

We define the utility associated with the generic training as:

$$U(i, g) = \mathbb{E}[w(i, g)|X_i] - C(i, g) + \varepsilon(i, g) \quad (3)$$

As choosing a generic training program does not require an occupation switch, the utility from this option does not depend on any occupation. This is equivalent to normalizing the utility associated with the generic training to i 's main past occupation.

⁵We interpret $F(j)$ as the relative costs to benefits, so that it includes also positive training features such as the probability of finding a job after training completion (*Job Finding Rate*). Individual-specific learning costs $\mathbb{I}[j = r]\gamma(i, o)$ play a role analogous to comparative advantage in a Roy model: they generate heterogeneous incentives to switch occupations, but through variation in the cost of acquiring new skills rather than in productivity once employed.

These parametric assumptions allow us to characterize reskilling decisions in closed form. A job-seeker chooses to reskill whenever the utility from doing so exceeds the utility from generic training:

$$\begin{aligned}
U(i, r, o) > U(i, g) &\implies \mathbb{E}[w(i, r, o)|X_i] - C(i, r, o) - \kappa(i, r, o) + \varepsilon(i, r, o) > \mathbb{E}[w(i, g)|X_i] - C(i, g) + \varepsilon(i, g) \\
&\implies \underbrace{\varepsilon(i, r, o) - \varepsilon(i, g)}_{\equiv \nu} > \underbrace{\mathbb{E}[w(i, g)|X_i] - \mathbb{E}[w(i, r, o)|X_i] + C(i, r, o) - C(i, g) + \kappa(i, r, o)}_{\equiv Q} \\
&\implies \mathbf{P}(j = r) = \mathbf{P}(\nu > Q) = 1 - \mathcal{F}(Q)
\end{aligned}$$

Given the assumption that the taste shocks $\varepsilon(r, o)$ and $\varepsilon(g)$ are i.i.d. type I extreme value, their difference ν follows the logistic distribution $\mathcal{F}$. Section 6 exploits this result empirically.

We now characterize the willingness to pay for reskilling (WTP) by comparing two options that have identical fixed learning costs except for the price of the actual training. Let $p(j)$ denote the price per hour (€/hour). Holding all non-price features constant, the compensating variation that equalizes indirect utility when moving from g to r solves: $U(i, r, o) - U(i, g) = \beta_p (p(r, o) - p(g)) + (\mathbb{E}[w(i, r, o)] - \mathbb{E}[w(i, g)] - \gamma(i, r, o) - \kappa(i, r, o)) = 0$. This expression leads to our structural equation for the reskilling WTP:

$$(p(r, o) - p(g)) \equiv WTP(i, r, o) = \frac{-(\mathbb{E}[w(i, r, o)] - \mathbb{E}[w(i, g)] - \gamma(i, r, o) - \kappa(i, r, o))}{\beta_p} \quad (4)$$

The WTP depends positively on the beliefs on the income shocks $\mathbb{E}[w(r, o)] - \mathbb{E}[w(g)]$ and negatively on the individual-specific learning costs and non-pecuniary switching costs.

In the empirical part of the paper we measure each element of this equation through survey data (see Section 4.1.3). Our randomization of the target occupation o further creates experimental variation in occupation-specific amenities, enabling a comparison of how beliefs, learning costs, and identity costs translate into differences in the WTP for reskilling across occupations. In addition, our randomized interventions generate exogenous variation in the core components of the framework. The information treatment acts as a shock to ΔW by shifting beliefs about entry wages in the destination occupation o . The mindset treatment, by contrast, is designed to reduce switching costs—either by lowering perceived learning effort or by easing identity-related concerns about entering a new occupation.

4 Data, Survey Design, and Measurement Validation

4.1 Survey overview

We first collect information on respondents’ employment and training history, self-reported skills, the role of past work in their identity, job search and expectations about wages, hiring chances, and employer demand in their main searched occupation. Each respondent is then randomly assigned a target reskilling occupation—IT support specialist or construction technician—which defines the occupation featured in their choice tasks. We also elicit expectations, perceived identity fit, and different perceptions (e.g., on social status or gender appropriateness) for this target occupation.

Participants then complete a discrete choice experiment (DCE) in which they evaluate pairs of training courses that vary exogenously in their features. Each choice scenario includes a generic training course (i.e. general skill upgrading) and a reskilling course (i.e. training for the assigned occupation), as well as an option to take no course. Finally, we test whether reskilling engagement is malleable through two light-touch interventions: an information treatment providing data on wages and hiring prospects, and a mindset treatment aimed at reducing perceived switching costs.

We next describe the randomized assignment of target occupations, the DCE design, and the survey measures corresponding to the model components. Figure A1 shows the structure of the survey, Table B1 describes the main survey questions used in the analysis and Section 7.1 describes our randomized interventions.

4.1.1 Randomization of target occupations

After screening, we randomly assign respondents to one of two high-demand occupations—IT support specialist or construction technician—with assignment stratified by gender (Figure A2). We refer to this as the respondent’s *treatment* occupation.

These occupations were selected because they are in high demand in Italy and across Europe. In 2023, both sectors recorded among the highest vacancy rates in Italy (Figure A3); across the euro area, construction and ICT ranked second and third, respectively, in average vacancy rates (Figure A4). Demand for ICT support technicians has risen with firms’ adoption of new technologies, while job growth in construction is driven by green-transition policies and investments under Italy’s recovery plan (Popp et al., 2020; Guiso et al., 2024). In Lombardy, the main region where participants in our study come from, IT and construction technician roles ranked first and fourth in online vacancy rates in 2022 (Wollybi/Lightcast data).

To ensure respondents knew what their treatment occupation entails, we showed a short video describing typical tasks and working conditions. Both roles were explicitly presented as white-collar, office-based (e.g., involving technical tasks such as design/coordination, site planning, compliance) and suitable for all genders. This clarification was particularly important for construction technician to distinguish it from manual site labor (Strandberg and Josephson, 2005). All reskilling courses in the discrete choice module are tailored to the assigned occupation—e.g., IT respondents viewed IT courses, and construction respondents viewed construction courses.

4.1.2 Discrete choice experiment

Our DCE aims to estimate participants' willingness to pay for reskilling relative to generic training, controlling for other key program features such as duration or delivery mode. The DCE allows us to simulate realistic trade-offs that jobseekers face, recover the value individuals place on each attribute through WTP estimates, and isolate demand in a controlled setting. By randomly varying program attributes, we identify the causal impact of each feature on training decisions and capture heterogeneity in preferences across individuals.

Each respondent completes six choice scenarios, in which they are asked to choose between generic training in "Microsoft Office" (which was one of the most popular options among jobseekers at the time of the survey, according to our partner organization), reskilling in the treatment occupation, or no training at all (an "opt-out" option). Besides their generic vs. occupation-specific content, each program is also characterized by a bundle of features: duration (80, 200 or 500 hours), setting (virtual or in person), price (€1.17 or 1.67 per hour, paid by the participant or the training provider), monetary subsidy (0, €1.72 or 3.44 per hour), structure (flexible or full-time), and job finding rate among participants upon completion.⁶ In our theoretical framework, generic training in "Microsoft Office" and reskilling correspond to options g and r , respectively, while all the other course features are included in function $F(j)$.

Program attributes are exogenously varied across scenarios. To reflect real-world differences in training markets, reskilling programs are designed to be longer and more employment-oriented than generic training. Specifically, reskilling courses last 200 or 500 hours with job-placement rates of at least 50%, while generic courses have a duration of 80 or 200 hours, and job-placement rates start at 23%. This

⁶We selected these features based on consultations with job counselors and focus groups with jobseekers, aiming to keep them close to real training options in Italy while ensuring they were not cognitively taxing for respondents. The specific attribute levels were informed by a benchmarking exercise of existing training programs at the national level. For example, the cost-per-hour levels were derived by taking posted prices of well-known courses in Italy and dividing them by their duration. Figure A5 shows an example of choice scenario and Figure A6 shows the different feature levels.

structure mirrors actual trade-offs between effort, duration, and expected returns between the two types of courses. Choice scenarios are identical across the two treatment occupations (IT and construction).

We constructed the choice scenarios using a D-efficient experimental design to maximize statistical precision while minimizing respondent burden.⁷ The final design comprised 18 choice sets divided in three blocks. Each respondent was randomly assigned one block (i.e. six choices). We also randomized the order of appearance of course attributes by having three possible ordering variants for each block, making it less likely that respondents consistently overlook a particular attribute. Empirical checks confirm balance of levels within and across blocks, and no correlation between factors (Figure A7).

4.1.3 Empirical measures of reskilling, expected returns, learning and identity costs

To measure reskilling intentions/demand, we use respondents' stated choices from the DCE (i.e. whether they pick the reskilling option as their favorite in a given choice scenario). In addition, for half of our survey sample, we can observe their real-life training and reskilling from administrative data (see Section 7.3). We construct proxies for each component of our framework of Section 3 as follows:

- **Learning costs ($\gamma(o)$).** We measure both actual and perceived skill distance from the treatment occupation. Actual distance is the share of O*NET skills in the treatment occupation that overlap with those of the respondent's past occupation; perceived distance is based on a checklist of O*NET skills respondents report already possessing for the treatment occupation.⁸
- **Expected returns ($\mathbb{E}[w(r, o)]$ and $\mathbb{E}[w(g)]$).** For both the searched and treatment occupations, we measure the expected wage and hiring probability within three months. ΔW includes the difference in both wages and hiring likelihood between treatment and searched occupations.
- **Identity fit costs ($\kappa(o)$).** We elicit perceived identity fit with, and perceived social status of, the treatment occupation. We also asked about the identity fit in the respondent's main past job.⁹

Table A5 shows the correlation between these empirical measures. Most correlations are small, suggesting that the measures effectively reflect different underlying components.¹⁰

⁷This method maximizes the D-efficiency of the design based on the variance-covariance matrix of the parameter estimates of the conditional logit model (Cook and Nachtsheim, 1980; Zwerina et al., 1996; Carlsson and Martinsson, 2003). We set priors at zero.

⁸In the survey, respondents describe their main past job and key tasks in open text; we use Lightcast's natural language processing model to map these descriptions to ISCO codes and corresponding O*NET skill profiles. For respondents who never worked in the past, we compute skill distance from their main searched occupation. See Appendix B for additional details, and here for the O*NET data.

⁹For perceived identity fit, we ask: "How well do you believe this job matches your own identity and self-perception?" (scale 1-10)". For social status, we ask the agreement with: "The treatment job is associated with a low social class". For identity fit in the past job, we used a scale of four items (adapted from Welbourne and Paterson (2017)).

¹⁰The survey also asked: "How capable do you think you are of doing this job (i.e., the reskilling target job) with your current

4.2 Survey Samples

We conducted the survey with two samples of Italian jobseekers:

Survey company sample. We worked with a professional survey company (CE&Co), which runs a panel of 150,000 members, representative of the entire Italian population.¹¹ From this panel, we randomly sampled respondents to reach a target of 600 completed interviews by unemployed jobseekers aged 18-55, currently looking for a job and not undertaking a training. Quotas were used in order to align the sample composition with Italian unemployed jobseekers' age, gender, and geographical area (according to information from the Labor Force Survey by the Italian statistical institute, ISTAT).¹²

AFOL sample. The second sample was recruited through our field partner AFOL Metropolitana ("AFOL" hereafter), the consortium of all public employment agencies in the metropolitan area of Milan. AFOL provides jobseekers with free services including career guidance, job search assistance, training, and administrative support. AFOL staff invited jobseekers registered between January 2022 and July 2023 to participate. We excluded individuals without an email address, of foreign nationality, outside the 18-55 age range, and—among those registered after September 2022—with an active employment contract. Invitations were sent in three waves between April and September 2023.¹³ The target population included 44,224 jobseekers, of whom 512 completed the survey, implying a response rate of 1.2%.¹⁴

The survey took on average 20 minutes and all respondents completing it were compensated.¹⁵

4.3 Summary Statistics

Table A1 reports summary statistics by gender, and Table A2 by gender and sample. Respondents are on average 40 years old, 16% have lower-secondary education and 27% hold a college degree. Most have prior work experience and have been unemployed for about 40 months.¹⁶ Half are searching for

skills?", which we label "Confident can do job" in Table A5. We pre-registered this variable as a component of our skills index. However, empirically, this measure is much more strongly correlated with identity-related measures ($\rho = 0.72$, $p < 0.001$) than with our other skill measures ($\rho < 0.05$, $p > 0.10$; see last row of Table A5). Given this ambiguity in interpretation, we include this variable as a control in our main analyses but do not use it as a proxy for skills. Results are robust even when not including it.

¹¹Panelists are recruited through both in-person and online channels, and identity checks are done at enrollment.

¹²Invited panelists received a personalized survey link by email, which could be used only once. We implemented several real-time quality checks: automated filters excluded responses completed in less than 25% of the median time, those showing uniform answers across scales, or those containing internally inconsistent responses.

¹³Separate survey links were used for jobseekers registered before and after September 2022, when AFOL introduced a new onboarding procedure. Assignment to the survey and treatments was stratified accordingly.

¹⁴This figure represents a lower bound due to invalid email addresses. Comparable online surveys with public employment services samples report similar rates: Leduc and Tojerow (2025) document a 5% click rate, while DellaVigna et al. (2022) report a 9% response rate for mail and SMS invitations.

¹⁵For the survey company sample, participants received tokens redeemable through the company, worth approximately five euros. For the AFOL sample, the first 500 respondents received a €5 Amazon voucher.

¹⁶We asked two questions about unemployment duration: one about how long a respondent had been unemployed since finishing education, and one about the length of their current unemployment spell. On average, respondents reported roughly 30 months for the first and 40 months for the second. Because these figures are similarly high, we interpret both answers as approximations of total time spent unemployed over one's life, rather than distinct spells. The reported unemployment length

the same occupation as their main past job, but the majority express willingness to accept jobs outside their main searched target. 55% have previously participated in training. Respondents expect a 42% probability of finding a job in their search occupation within three months, rising by 11 percentage points if trained. Respondents' previous jobs are concentrated in clerical support and service or sales roles (40%), and 2% have prior experience in the treatment occupations. In terms of skills, respondents report having around 70% of the skills needed in the treatment occupation. Gender differences are modest: women are more likely to have children and to mention caregiving as a reason for not working, but training history, job-search behavior, and beliefs about employability are similar for men and women.

Representativeness. Table A3 shows that, relative to the population of jobseekers registered in the AFOL job centers, our sample of AFOL respondents is slightly older, more educated, and has a higher share of women. Table A4 compares our two survey samples with the national unemployed and inactive population using the EU Labor Force Survey (LFS, 2022). Respondents are, on average, older and better educated than the national benchmark, while partnership and parenthood rates are similar. The main differences concern unemployment duration and support. Participants from the survey company have been jobless the longest (on average 55 months) and 20% of them receive any form of government support. The AFOL sample shows shorter unemployment spells (22 months), but also higher subsidy reception (65% of the sample). The national averages are between these two samples. To account for these differences, all our regressions include sample fixed effects, and Appendix C confirms that results are robust to weighting for representativeness at the country level. Estimates should be interpreted as internally valid for our study population, and we discuss external validity in the Conclusion.

4.4 External Validation of Training Choices

While the reskilling choices in our DCE are hypothetical, we validate that they meaningfully capture real behavior in two ways. First, we designed the survey to encourage realistic decision-making. Respondents were explicitly asked to consider the choices they would make in real life, taking into account their actual financial and time constraints, and were told that there were no “right” or “wrong” answers—but that we were only interested in what they would personally choose.

Second, we show empirically that hypothetical choices are correlated with real and incentivized behavior within the AFOL sample. In an additional task, respondents were asked to allocate ten points across actual training courses available in the Lombardy region, choosing how much they would “in-

may include periods of undeclared (“off-the-books”) work, which is common in Italy (Boeri and Garibaldi, 2002).

vest” in each. To encourage truthful responses, we informed participants that their responses might be shared with their assigned job-center caseworker to guide their counselling. Those who expressed a stronger preference for reskilling in the DCE also allocated more points to reskilling courses in this real-world list ($\beta = 0.11$, $p = 0.07$). Using administrative data, we further find that individuals with higher predicted DCE participation in training are significantly more likely to have enrolled in courses over the past two years ($p < 0.10$). Together, these results indicate that our hypothetical choice measures provide a credible proxy for real-world reskilling intentions and behavior.

5 Three Facts about Reskilling Intentions

This section documents three empirical facts about reskilling intentions in our sample of Italian job-seekers. In line with our framework, we show that these intentions are shaped by a combination of expected returns, learning and identity-related switching costs. Note that these results are based on our control sample ($N=376$), that is the set of respondents that were not involved in the experimental treatments described in Section 7.1. We always control for the different data collection samples across all regressions.

Fact 1: Not Everyone Wants to Reskill

Figure 1 shows the individual-level frequency of choices for different types of courses. Intentions to train are quite high in our sample. Overall, we find that respondents choose a course in almost 3 out of 4 choices (74%), and they pick the no-course option only in 26% of their choice scenarios. When comparing choices between generic training and reskilling, we find that the share of respondents selecting each option is nearly identical. Respondents choose the generic training as their preferred option in 36% of their choice scenarios, and reskilling in 38% of them ($p = 0.27$). This occurs despite reskilling courses leading to higher job finding rates on average. Hence, on average, jobseekers are indifferent between upgrading general skills or investing in occupation-specific reskilling.

Fact 2: There is Large Heterogeneity in Reskilling Intentions by Target Occupation

Reskilling intentions vary markedly with the sector of the target occupation. Respondents assigned to the construction or IT survey arms have similar opt-out rates ($p=0.3$), indicating similar overall intentions to get trained (Figure 1b). Yet, when it comes to choosing between reskilling and generic

courses, reskilling for the IT occupation is much more likely to be chosen over generic training than for the construction occupation ($p=0.00$).

Because wages, career prospects, and training features are identical across the two target occupations (by design of the DCE), the observed gap in demand must reflect factors other than economic returns or course supply. The evidence points to two forces: limited information about actual returns and non-pecuniary considerations—such as the perception that construction jobs carry lower social status or fit less well with one’s identity - compared with IT. We indeed find systematic differences in attitudes and perceptions between the two occupations (Figure 2): while participants expect higher wages in construction than IT, they are more pessimistic about their identity fit, skills and hiring likelihood in construction than IT.

Fact 3: Perceived Identity Fit Shapes the Costs of Reskilling

To investigate what correlates with respondents’ choice of reskilling vs generic training, we estimate an OLS model at the individual level, where the dependent variable is the share of choice tasks (out of six) in which a respondent selected reskilling as their preferred option. Our explanatory variables of interest map into the components of the utility function presented in Section 3, as outlined in Section 4.1.3. We further control for demographics (gender, age, and education) and other respondent characteristics such as unemployment duration, benefit receipt, region, time constraints, job search intensity and prior training experience.¹⁷

Figure 3a shows that perceived identity fit with the target occupation is the strongest predictor of reskilling intentions, both in magnitude and precision. A one–standard-deviation increase in identity alignment is associated with an eight–percentage-point rise in the probability of choosing reskilling—about 22% of the average reskilling rate.

Beliefs about job prospects, learning costs, and demographic characteristics also influence reskilling intentions, though their effects are smaller than that of perceived identity fit. Respondents who expect higher wages or stronger employer demand in the target occupation are more willing to reskill, while perceiving it as low status dampens interest. Learning costs, proxied using prior work experience, play a minor role: only the share of self-reported skills relevant to the target occupation shows a significantly positive association with reskilling, but not actual similarity.¹⁸ Finally, being over 40 significantly lowers

¹⁷In particular, the regression controls for treatment occupation, data-collection sample (CE&Co or AFOL), randomization block, region of residence, length of unemployment, past occupation dummies, and all the regressors displayed in Figure A9a.

¹⁸Compared to self-reported skills, identity fit, and expected returns—all elicited through direct questions—actual skill distance may contain more measurement error because it requires mapping past occupations to *O*Net* codes. However, we view it as a reasonable proxy, reflecting the type of information job centers typically use when matching jobseekers to training.

the likelihood of choosing reskilling—consistent with shorter career horizons lowering the expected value of engaging in training (Ben-Porath, 1967).¹⁹ Figure 3b shows that identity-related switching costs are the most important predictor of reskilling within the construction occupation, only followed by age. In IT, perceived identity fit shows a correlation with reskilling that is comparable in magnitude to age, expected wages, social status, and education.

A Lasso regression using all predictors confirms the centrality of perceived identity fit: it is the only variable selected as a significant predictor of reskilling, both in the full sample and when the model is estimated separately for each occupational arm. Taken together, these results indicate that identity-related switching costs are a primary barrier to reskilling, outweighing standard pecuniary or effort-based factors.²⁰

Summary. These three facts align with the set-up of our theoretical framework, which focuses on expected returns, learning costs and perceived identity fit as key factors in the choice of reskilling. They also highlight the relative higher importance of identity-related costs in participants’ choices. We now turn our analysis to the empirical estimation of the WTP for reskilling, which allows us to control for differences in training features and attach a monetary value to reskilling.

6 Estimating the Willingness to Pay for Reskilling

6.1 Empirical Models

We use two main models to quantify the willingness to reskill among our respondents, and benchmark it against preferences for other course attributes. As in the previous section, we estimate these models on the *control group*—respondents not exposed to the treatments described in Section 4.1.2—to recover undistorted preferences over attributes.

Baseline specification: conditional logit. We estimate a conditional logit model to quantify how course features shape training choices *ceteris paribus*. Following standard random-utility frameworks, individ-

¹⁹Women appear less willing to reskill in bivariate models, yet this difference vanishes in the multivariate regression when controlling for perceived identity fit and expected wage.

²⁰Figure A9 shows the coefficients for a more comprehensive set of predictors of reskilling. Table A7 compares the explanatory power of our survey variables on respondents’ choices of generic training versus reskilling through a multinomial logit model. Most variables that predict reskilling choices—such as identity fit and age—do not predict generic training in the same way. While the signs are similar in many instances (e.g., being older predicts lower engagement in both reskilling and training), the marginal effects on generic training are usually smaller and non-statistically significant. This suggests that the drivers of reskilling are distinct from those of general training.

ual i derives utility $U_{ij} = V_{ij} + \varepsilon_{ij}$ from alternative j , where V_{ij} is the systematic component (i.e. a linear function of observable individual characteristics and course features) and ε_{ij} an idiosyncratic shock. The systematic utility is specified as:

$$V_{ij} = \alpha_j + \beta_1 \text{Reskilling}_j + \beta_2 \text{Cost}_j + \beta_3 \text{JFR}_j + \beta_4 \text{Duration}_j + \beta_5 \text{Delivery}_j + \beta_6 \text{Timing}_j + X_i \Gamma + \varepsilon_{ij} \quad (5)$$

where course attributes vary at the alternative j level, the alternative-specific constant α_j captures the mean utility of each option, including the no-course choice, and X_i is a vector of individual characteristics examined in the previous section (Train, 2009).²¹ We assume ε_{ij} follows an i.i.d. type-I extreme-value distribution. This structure allows variation in course attributes within choice sets to identify the marginal utilities β_k , net of individual heterogeneity.

Logit coefficients are identified only up to scale. To gauge the size of our estimated coefficients, we report willingness to pay measures, expressed as ratios of attribute coefficients to the marginal utility of cost ($-\beta_2$). Each WTP represents the euro amount per hour that keeps expected utility constant when a course feature increases by one unit (or changes discretely from one level to another). For example, for reskilling: $\text{WTP}(\text{Reskilling}) = -\frac{\beta_1}{\beta_2}$.

Heterogeneous preferences: mixed logit. To assess how unobserved heterogeneity shapes the evaluation of reskilling and other course attributes, we extend the baseline model to a mixed logit that allows coefficients to vary randomly across individuals. Let individual i 's utility from alternative j be:

$$U_{ij} = \sum_{k=1}^K \beta_{ik} X_{jk} + \varepsilon_{ij}, \quad (6)$$

where β_{ik} represents the individual-specific marginal utility for attribute k . We assume β_i follows a continuous distribution $f(\beta)$, taken to be multivariate normal: $\beta_i \sim \mathcal{N}(b, W)$. The resulting probability that individual i chooses alternative j is:

$$P_{ij} = \int \left(\frac{e^{\beta x_{ij}}}{\sum_m e^{\beta x_{im}}} \right) \phi(\beta | b, W) d\beta \quad (7)$$

where $\phi(\beta | b, W)$ denotes the multivariate normal density. This formulation integrates over the pop-

²¹For identification, we exclude the constant for the second alternative. X_i includes: treatment occupation, age, gender, block, length of unemployment, education, dummies for past occupation, time constraints, job search intensity, past training dummy, actual and perceived skill distance, expectations on demand for the treatment and searched jobs, differences between treatment and searched occupations in expected wages and job finding probabilities, identity fit in treatment and past job, perceived social status and confidence in doing the treat job, survey sample, and geographical region of residence. Cost_j is the out-of-pocket expenditure bore by the respondent: it includes both price and subsidy and can thus be negative. When the price is paid by the provider we code it as a subsidy, i.e. it enters negatively in the Cost_j definition.

ulation distribution of preferences, so the estimated model recovers both the mean and dispersion of marginal utilities across individuals. This model enables the recovery of the full distribution of WTP measures, rather than a single mean effect as in the conditional logit. We estimate the model by maximum simulated likelihood. While less efficient than a standard logit, the simulation-based approach offers a richer depiction of preference heterogeneity.

6.2 WTP Estimates for Reskilling

Baseline results: conditional logit. Table 1 reports the estimated marginal utilities pooling both treatment occupations. Consistent with the patterns documented in Section 5, the average marginal utility of reskilling is small and statistically insignificant (0.002, $p > 0.10$), implying a willingness to pay close to zero (see Column (1) of Table 2, where we convert coefficients into monetary units). This aggregate result, however, masks substantial heterogeneity by target occupations. Columns (2) and (3) of Table 2 show that respondents are willing to pay about €3.5 per hour to reskill into IT, whereas they would require compensation of roughly €5.3 per hour to reskill into construction. These differences underscore the role of occupation-specific attributes in shaping reskilling preferences.²²

Heterogeneity by perceived returns, learning costs, and identity fit. Figure 4a shows that beliefs about job demand and learning costs are particularly relevant for the WTP to reskill in IT. Respondents who perceive high demand by employers in IT exhibit an average WTP of €6.3/hour, compared to €0.7/hour among those with low perceived demand. Similarly, respondents reporting low skill distance from the treatment occupation display a WTP of €7/hour, versus €1.9/hour among those with high learning costs. In contrast, reskilling into construction remains unattractive regardless of perceived demand, wage expectations, or learning costs—suggesting that other frictions dominate in this sector.

The most pronounced heterogeneity—for both sectors—arises from identity fit. Respondents with below-median perceived identity fit require substantial compensation to reskill: €10.4/hour in construction and €2.3/hour in IT, highlighting identity fit as a key psychological barrier to switching occupations. Among those with above-median perceived identity fit, WTP is positive for both occupations and larger than €6/hour. Perceived social status exerts a similar influence across sectors, further reinforcing the role of non-pecuniary switching costs in shaping reskilling preferences.

²²A potential concern is that the generic Microsoft Office course may feel closer to reskilling in IT than in construction, creating an anchoring effect that makes the shift to IT appear smaller—and the shift to construction larger—than in reality. Because the target occupation is randomized across respondents, this does not affect within-person comparisons, and the large WTP differences we observe are unlikely to be driven solely by this anchoring.

Heterogeneity across demographic groups. Figure 4 displays WTP estimates by respondent demographic characteristics. Preferences for construction vary sharply: women require a compensation of roughly €7.1/hour to participate, while men’s average WTP is close to zero. Educational differences are similarly large: non-college respondents exhibit modest positive WTP (€1.5/hour), whereas college graduates demand compensation of €5.6/hour. Both older and younger respondents have a negative WTP for construction, with older adults showing a stronger aversion. By contrast, differences in WTP for IT reskilling are much smaller. All demographic groups value IT training positively. Men are willing to pay more (€5.7/hour) than women (€3/hour), and older respondents also value IT slightly more (€5.2/hour) than younger respondents (€3.7/hour).²³

Distributional results: mixed logit. Figure 5 plots simulated WTP distributions by treatment occupation and respondent characteristics, illustrating how the sources of heterogeneity discussed above play out across the entire preference distribution. The WTP distribution for IT first-order stochastically dominates that for construction, indicating that jobseekers consistently assign higher value to IT reskilling across the entire preference spectrum (Figure 5a).

Among psychological and belief variables, the largest shifts in the WTP distribution occur by identity fit and expected demand (Figures 5e and 5b). Although average WTP differs little by wage beliefs, the WTP distribution is notably wider among those who expect high wages in the target occupation. This suggests that favorable wage expectations alone do not offset negative views about other occupation-specific attributes, concentrated in the WTP left tail (Figure 5c).

In terms of demographics, Figure 5g shows that men’s WTP distribution lies to the right of women’s, yet the substantial overlap between the two curves confirms that gender, while correlated with reskilling interest, does not fully account for variation in preferences. Differences by age and education are concentrated in the tails, with a subset of younger and college-educated respondents display particularly high WTP.

6.3 WTP Estimates for Other Program Features

Table 1 shows the marginal utility and Table 2 WTP estimates for the other program features varied in our DCE. As expected, training cost has a large negative effect on utility, while higher job finding rates strongly increase it. Using the estimated marginal effect of job finding rates and assuming a linear

²³Older respondents are less willing to reskill on the extensive margin (as shown in Figure 3a), for both IT and construction. The higher WTP for reskilling in IT among older respondents suggests that they find IT relatively more attractive than the generic Office course once they engage with the reskilling choice, even though they are generally less inclined to reskill overall.

relationship, a 10 percentage points increase in the job finding rate corresponds to a WTP of roughly €160 for a 100-hour course—slightly above the average course cost in our scenarios. Heterogeneity in this valuation is limited across occupations and demographics (Figure A14b), with one clear exception: younger respondents place significantly higher value on job-placement post training than older jobseekers.²⁴ Figure A14a further shows that respondents with more skeptical views of the target occupation—those perceiving lower social status, expected demand or weaker identity fit—exhibit higher WTP for placement rates after training, suggesting they require stronger evidence of returns before committing to reskill.

Other program attributes appear less important in participants’ choices. Respondents weakly prefer shorter courses, demanding about €1.7 in compensation for 120 additional training hours. In-person instruction is valued positively, particularly for IT, where jobseekers are willing to pay around €2.7 per hour for classroom compared to online delivery; the effect is negligible in construction. We find no systematic preference between full-time and flexible schedules.

6.4 Implied Market Shares and Counterfactual Exercises

Beyond individual preferences, the discrete-choice framework allows us to simulate training take-up under alternative course offers. We use the model to assess how wage changes, learning costs, and identity costs affect participation, and compare their influence with valued program features (i.e. JFR).

Baseline scenario. We first simulate predicted market shares in a baseline scenario that incorporates all elements of the model described in Section 3. Each individual chooses between a reskilling course and a generic training course, both characterized by attributes set at their average levels across our DCE scenarios (i.e. in terms of price, duration, and job finding rate)²⁵. Predicted utilities are computed using the estimated parameters from Equation (5). As in Equation 2, the utility of the reskilling option also includes the expected wage shock from switching occupations, $\mathbb{E}[w(r, o)] - \mathbb{E}[w(g)]$, average learning costs $\gamma(r, o)$, and identity costs $\kappa(r, o)$. The implied probability of selecting reskilling is:

$$PR_r = \frac{\exp(\hat{V}_r)}{\exp(\hat{V}_r) + \exp(\hat{V}_g) + \exp(\hat{V}_0)}, \quad (8)$$

where V_j denotes the deterministic component of utility for each alternative $j \in \{r, g, 0\}$, where r is reskilling, g is generic training, and 0 is no course.

²⁴Jobseekers show a slightly higher WTP for job finding rates in construction than in IT, coming from a lower price elasticity in construction ($\beta_{\text{cost}} = -0.08$ vs. -0.11).

²⁵In our model, the price can be negative due to the presence of subsidies. For the exercises in this section, we use an average positive price, i.e. when it entails an out-of-pocket expenditure borne by the respondent and no subsidy.

Decomposing structural forces. We perform counterfactual exercises that sequentially shut down each structural force—wage shocks, learning costs, and identity costs—to assess their contribution to reskilling participation. For each case, we compare the resulting change in the predicted reskilling share to the baseline (where reskilling has a market share of 27%), and compute the equivalent price change that would generate an identical change in participation. Results are presented in Figure 6a.²⁶

Among the structural forces outlined in our framework, shutting down identity costs produces the largest change in reskilling participation—about 27 percent relative to baseline—while removing wage shocks or learning costs has much smaller effects. The equivalent price decrease needed to replicate the same change is roughly 267 percent of the average hourly training cost, underscoring the economic magnitude of identity-related barriers. Yet, the job finding rate plays the most important role: shutting it down would more than halve the baseline reskilling share, an effect on par with increasing the hourly price by more than sevenfold. Figure A13 shows the same exercise by treatment occupation. Identity-related costs explain around 30% of the predicted reskilling take-up in IT and around 35% in construction.

Intensity of structural frictions. In a second counterfactual exercise, we focus on the intensive margin and examine how the reskilling share responds to changes in the magnitude of each structural force or the job-placement rate. For this exercise, each channel is represented by a single proxy: the expected wage differential for wage shocks, the actual skill ratio for learning costs, and perceived identity fit with the treatment occupation for identity costs. Holding all other baseline-scenario parameters constant, we vary the wage shock, learning costs, identity costs and job finding rate across deciles of their empirical distributions and recompute the predicted reskilling share (Figure 6b). Participation falls sharply with higher identity costs and lower job finding rate post training but remains largely stable across wage-shock and learning-cost deciles.

6.5 Summary

In this section, we quantified jobseekers’ willingness to pay for reskilling and a broad range of program features. On average, respondents are willing to pay for IT training but need to be compensated to reskill as construction technicians—even when program design is held constant. This underscores the

²⁶When a given channel is captured by multiple components, we shut it down in the counterfactual by setting all associated terms to zero. Specifically, we eliminate wage-related effects by setting both the expected wage differential and the expected hiring-probability differential between the target and searched occupations to zero; learning costs by setting both actual and perceived skill-distance measures to zero; and identity costs by setting perceived identity fit with both the target occupation and the respondent’s main past occupation to zero.

need to tailor training policies to specific occupations. Additionally, age, concerns related to identity fit and beliefs about returns predict differences in WTP for reskilling within treatment occupations. Finally, jobseekers place great value in job finding rates post-training, even conditional on choosing programs targeted to in-demand occupations.

These demand-side factors suggest that reskilling policies that account for workers' preferences—either by tailoring program design or through better targeting—could substantially increase take-up. Our analysis also highlights the role of information and identity-related concerns in the willingness to switch occupations through reskilling. This raises the possibility that interventions addressing limited information on returns or reducing perceived non-pecuniary switching costs may influence reskilling intentions.

7 Can the Demand for Reskilling be Shaped?

Building on the WTP patterns documented in Section 6, we examine whether light-touch interventions designed to address informational, learning and psychological frictions can increase reskilling intentions and translate into changes in real-world training and employment outcomes.

7.1 Experimental Design

Right before the DCE, we randomize respondents into the following three groups:

1. INFO (N=369): we provide information on the level of vacancies and on the average wage in the treatment occupation. As shown in Figure A15a, we communicated the absolute number of vacancies in the treatment occupation and compared it with the number of vacancies in the median occupation in Lombardy (for the AFOL sample) or in Italy (for the survey company sample).²⁷
2. MINDSET (N=367): respondents are shown a “success story” of a woman who succeeded in switching to a new occupation after a training program and learn about the concept of “growth mindset”, which facilitates learning a new skill at any age (see Figure A15b).
3. CONTROL (N=376): no additional information is provided.

Both the INFO and MINDSET treatments were delivered via short (1–2 minute) narrated videos with voice-over slides and the same narrator. Respondents could skip the video but were then asked

²⁷For jobseekers in the AFOL sample, the number of vacancies for the IT (construction) occupation was 20 times (2 times) greater than the median number of vacancies. For jobseekers in the survey company sample (across Italy), the number of vacancies for the IT (construction) occupation was 14 times (2 times) greater than the median number of vacancies.

comprehension questions; incorrect answers triggered a prompt to rewatch the video. We recorded viewing time and responses to the comprehension checks. Treatment assignment was randomized at the individual level within each gender-occupation group (e.g., women-IT). We use these treatments to examine changes in both stated reskilling intentions and real-life behavior.

Balance Table A9 shows treatment-assignment balance checks. Column (4) shows the p-value of an F-test on the joint significance of the set of treatment dummies in explaining the row variable, controlling for stratification variables. According to the F-tests, we find imbalances on 6 out of 30 variables, but differences are small in magnitude across treatments and decrease to 3 out of 30 when considering the MHT-corrected p-values (reported in Column 6).

7.2 Impacts on Reskilling Intentions and Willingness to Pay for Reskilling

Empirical model. To test whether our light-touch treatments are effective in changing participants' reskilling choices in the survey, we use the following model:

$$y_{ij} = \alpha + \beta_1 T_i^{info} + \beta_2 T_i^{mind} + \delta X_{ij} + \gamma Z_i + \phi S_i + \epsilon_{ij}$$

where y_{ij} is respondent i 's choice in scenario j , e.g. a reskilling choice. T_i^{info} and T_i^{mind} are indicator variables for being assigned to the INFO or MINDSET treatments, respectively. The vector X_{ij} contains the difference in features between the two courses shown in scenario j (cost, delivery, structure, subsidy, job finding rate and order of appearance), Z_i contains controls about the respondent (age, region, education, whether they are searching for their past job, having any kids, having participated in any course in the past, and interest in the treatment occupation) and S_i stratification variables (gender, treatment occupation, survey sample and block of choice scenarios).²⁸ Standard errors are clustered at the individual level. Our coefficients of interest, β_1 and β_2 , provide the percentage points increase in the likelihood that i chooses a certain training option, e.g., reskilling, in choice scenario j .

Reskilling intentions Table 3 shows the main results of our experiment. Column (1) of Panel A shows that providing information on the wage of and demand for the treatment occupation increases the likelihood of choosing reskilling by 4.4 percentage points ($p=0.03$), which represents 11% of the mean of the dependent variable. Columns (2) and (3) show that the effects are larger for the IT than the construction occupation, though the difference between the two effects is not statistically significant. Columns (4)

²⁸Table C3 shows the same results reweighted to improve representativeness, while Table A11 shows the results using additional controls (the same as in Figure A9a).

to (6) adjust the estimates to take into account respondents' limited attention to the intervention video. Column (4) excludes respondents who spent too little or too long on the video page, Column (5) only keeps individuals who watched the entire video and Column (6) controls for whether the person replied wrongly to at least one understanding question after the video.²⁹ Reassuringly, independently of the specific adjustment, we find very similar results for the effect of information provision.

The second row of Panel A in Table 3 shows that the mindset treatment has no effect on the likelihood of choosing reskilling among our respondents. A plausible reason is that the intervention was too light to be able to change ingrained attitudes about someone's perceived identity fit across occupations and/or perceptions of learning costs. This evidence resembles the results in Delfino (2024), who also show that an informational treatment is more effective than an identity-focused message to encourage men in caring sectors, and of Belot et al. (2024).

Panel B of Table 3 shows that the information treatment does not change the likelihood that respondents choose any training course as opposed to the no-course option. This evidence confirms that the content of the informational video was interpreted by viewers as being related to the treatment occupations, and that the video did not convey additional signals about the value of training in general.

Heterogeneity and demand bias. Given the positive average effect of information, a natural question is who responds most—and whether this reflects genuine belief updating rather than demand bias. Table 4 explores this issue by looking at differences based on respondents' prior beliefs on the wage and perceived identity fit in the treatment occupation. Columns (1)–(3) show that the effect of information is concentrated among those who initially underestimated wages. After learning about the (higher) actual wages, this group becomes more likely to choose reskilling. This supports the idea that belief updating—not demand bias—drives the effect. Columns (4)–(5) show that the information treatment has no effect among respondents with low perceived identity fit, but significantly increases reskilling intentions among those who feel closer to the target occupation. This pattern suggests that non-pecuniary switching costs are important as they can also mediate the effectiveness of informational interventions. The mindset treatment shows no effect even when conditioning on high vs low levels of perceived identity fit.

Willingness to pay for reskilling. We next test whether the information and mindset treatments change how much respondents value reskilling. Because the randomized interventions were administered be-

²⁹Understanding checks asked about the statistics provided by the video (for the INFO treatment) and about the meaning of growth mindset (for the MINDSET treatment). The proxies of respondents' limited attention are balanced across treatments.

fore the DCE, we can estimate their effects on willingness to pay for reskilling within our choice model. Figure 7a shows that the information treatment substantially increases the WTP, whereas the mindset treatment (Figure 8a) has no detectable effect. The increase in WTP under the information treatment is concentrated in the upper part of the distribution, suggesting that a sizable share of respondents—those strongly disliking the treatment occupation—remain unresponsive to new information. To gauge the magnitude of the effect, Figure A12 shows that the information treatment closes about 33% of the gender gap in WTP for reskilling at the median of the gender-specific distributions.

Consistent with the extensive-margin results shown in Table 3, the WTP shift induced by the information treatment is larger for IT than for construction (Figure 7b). As in the pooled sample, WTP for reskilling in IT does not change in the lower tail. In construction, however, the information treatment widens the overall WTP distribution, with both the lower and upper tails enlarging. Some respondents reduce their valuation of reskilling after receiving information about the construction occupation’s labor market returns. A possible reason is that they react against being nudged toward an unattractive occupation or the video makes them focus more - by contrast - on its less appealing aspects.³⁰ Other respondents markedly increase their valuation of reskilling in construction. Such long right tail is driven by young non-college respondents, who react most positively to the new information but represent a small share of the sample.³¹

Why does information work, but expected returns weakly explain reskilling intentions? In our discrete choice estimates, differences in expected wages and hiring likelihood (Δw) explain only a small share of variation in reskilling take-up (see Section 6.4). At first glance, this might suggest that jobseekers are largely unresponsive to economic incentives. However, survey evidence reveals that many participants hold compressed beliefs about both wages and hiring prospects in the target reskilling occupations. Figure 2 shows that 75% of respondents underestimate wages in the target occupations, and nearly 40% underestimate labor demand. We find similarly widespread misperceptions when we compare each respondent’s perceived returns to reskilling relative to their searched occupation—that is, the expected gain from switching from their currently searched occupation to the target occupation—with the corresponding actual returns using administrative data from their region.³² One in three

³⁰We find no evidence that the change in the left tail comes from respondents receiving “bad news,” i.e., those who had overestimated wages or job prospects in construction before the treatment.

³¹The right tail in the construction arm is consistent with the weighted results in Table C3, where the information treatment has a larger and statistically significant effect, though not distinguishable from the IT estimate.

³²We compare survey-based expectations of earnings and job-finding probabilities with actual earnings in the searched occupation (CICO) and actual vacancy rates (Lightcast). Actual returns are defined as the log wage difference between the target and searched occupations, weighted by the regional occupation-specific job-finding probability (as proxied by vacancy rates). Perceived returns are constructed analogously using survey measures. Individuals with positive actual but negative perceived

respondents underestimates the gains from moving away from their searched occupation compared to what regional administrative data suggest. These misperceptions compress the relevant variation in perceived returns, reducing the explanatory power of Δw in our WTP estimates. This interpretation helps reconcile the limited role of Δw in the choice model with the strong positive response to the randomized information treatment, which directly increased individuals’ beliefs about wages and hiring prospects in the target occupation.

7.3 Impact on Real-Life Training and Job Outcomes

The information treatment is effective in changing reskilling intentions within our survey. This section shows that the effect of this randomized treatment spills over into the participants’ real-life choices.

Administrative data (for the AFOL sample). In addition to providing employment guidance, AFOL offers training and helps jobseekers access to regionally funded courses across Lombardy. We link our survey to AFOL’s administrative records on participants’ employment and training histories. Employment data are supposed to cover respondents’ full job histories, and include information on the occupation and sector (at the NACE Rev.2 level) of each spell.³³ Training records span January 2022 to September 2024 and, for each training course a respondent enrolled in, we have information about its content and duration. As the survey was administered to the AFOL sample between April and September 2023, we can observe both pre- and post-survey actual training choices and employment. Using the official course titles, we classify each program chosen by participants as reskilling (courses teaching skills for a specific job) or generic training (courses on transferable or soft skills). We also flag whether each course targeted IT or construction, enabling us to track training related to the survey treatment occupation.

A key finding from these follow-up data is that none of the participants enrolled in construction-related training during the study period, mirroring the weaker reskilling intentions observed in the DCE. Given this absence of real-world take-up, we focus the remainder of the analysis on the control and IT treatment arms.³⁴

returns are classified as having biased beliefs. See Appendix B for details and a visual comparison of expected versus actual returns and costs.

³³We classify as “IT sector” macro-industries M and J (Professional, Scientific, and Technical Services; Information and Communication). Eurostat classifies these industries as “Knowledge-Intensive Services,” and most are considered “High-Tech.” See Table A10 for summary statistics from the admin data.

³⁴Results for the construction arm, available upon request, confirm the absence of any treatment effect on actual training.

Empirical model We create a balanced panel dataset with two periods for each person, before or after the survey. We use a difference-in-difference strategy to examine whether the respondent showed a change in training engagement after the survey, distinguishing between participants assigned to the information treatment or the control group using the following model:

$$y_{is} = \alpha + \beta T_i^{info} \cdot Post_s + \gamma Post_s + \gamma_i + \epsilon_{is}$$

where y_{is} is the outcome for respondent i who did the survey in date s . T_i^{info} is the indicator for being assigned to the INFO treatment and $Post_s$ is an indicator for the period after the survey. γ_i are individual fixed effects. Standard errors are clustered at the individual level. The outcome variables are defined as different types of engagement in training or employment take-up: reskilling for IT occupations, reskilling outside IT, generic training, employment in the IT sector, or employment outside IT. Our coefficient of interest, β , provides the differential change in the likelihood that i chooses a certain training, e.g., reskilling in IT, in the information treatment compared to the control, after participating in the survey.

Results Columns (1) to (3) of Table 5 show the effect of our information treatment on the within-person change in training engagement after the survey, in comparison with the control group. Column (1) shows that there is a 3.5 percentage points increase in the likelihood that a participant engages in a reskilling program related to IT after participating in our survey and receiving the information treatment, compared to participants who did not receive any information within the survey ($p=0.10$). This effect is substantial, considering that the mean engagement in reskilling in the control group in the period before the survey is 2% (see Table A10). Columns (2) and (3) show that this effect is only limited to IT reskilling courses, and does not extend to unrelated training options. Columns (4) and (5) show results on employment outcomes. Participants assigned to the information treatment are more likely to find a job in the IT sector (Column 4), whereas we do not detect any difference for any other job excluding IT (Column 5).

Taken together, these results suggest that information can shift real reskilling behavior, especially if it aligns with occupational preferences and accessible training opportunities. In contrast, information alone may be insufficient to overcome deeper barriers in less attractive sectors like construction.

8 Conclusion

This paper investigates how demand-related factors—related to skills, information and occupational identity—influence the decision to take up reskilling programs for two high-demand, entry-level occupations in Italy—IT support and construction technician—in a large sample of unemployed jobseekers.

Our findings suggest that traditional, generic supply-side approaches to boost training participation—such as expanding course availability—are insufficient to drive broad-based reskilling. Demand-side frictions, particularly those rooted in self-perception, identity, and information gaps, present meaningful barriers even in the presence of accessible and economically viable training options. Policies aimed at expanding participation must therefore address the psychological and informational constraints that shape individual decisions. Moreover, the strong influence of job placement rates on reskilling choices highlights the importance of aligning training offers with real labor market opportunities, possibly through tighter coordination between training providers and employers.

Our work speaks to research on labor reallocation and occupational mobility. Models of worker reallocation emphasize wage, productivity, and skill-adjustment frictions as key determinants of sectoral mobility and aggregate unemployment dynamics (e.g., [Artuç et al., 2010](#); [Carrillo-Tudela and Visschers, 2023](#)). Our evidence suggests that non-monetary factors—particularly identity-related switching costs—represent an additional, unaccounted source of rigidity in occupational adjustment. If workers perceive strong psychological or social barriers to changing jobs, aggregate reallocation may respond more sluggishly to shocks, even when monetary incentives to reskill are strong. Incorporating such identity-based frictions into models of labor mobility could therefore improve our understanding of why some displaced workers remain unemployed longer or fail to transition toward expanding sectors.

This paper contributes to the literature in three ways. First, it highlights the role of occupational identity and belief formation as central determinants of reskilling demand, helping to explain persistent gaps in training uptake that cannot be attributed to monetary factors alone. Second, it demonstrates the value of combining discrete choice experiments with randomized information treatments in understanding labor market behavior—an approach that complements traditional RCTs and can be implemented at scale. Third, it offers a framework for designing training policy interventions that are sensitive to individual heterogeneity in motivation, belief updating, and identity fit—elements increasingly relevant in dynamic labor markets shaped by automation and structural transformation.

While our study focuses on Italy—a country with low adult training participation and significant regional disparities—the mechanisms we identify are likely relevant across other OECD contexts. In-

formational gaps and identity-related barriers are not country-specific and may be especially salient in sectors undergoing technological transitions or marked by persistent gender and status imbalances. Our focus on IT support and construction technician was intentional: both occupations offer strong labor market prospects without requiring a college degree, yet differ sharply in social perceptions and remain heavily male-dominated. Although reskilling dynamics may differ in other fields, many high-demand occupations—such as healthcare—are also shaped by strong social identities and gender segregation. These parallels suggest our findings may extend beyond the country and occupations studied.

The external validity of our findings also depends on institutional features that shape adults' incentives to invest in new skills. Italy's fragmented training system and relatively low-quality signaling environment may amplify the value jobseekers place on job-placement guarantees or credible information. In settings with stronger guidance systems, tighter quality control, or more structured apprenticeships, informational frictions may be weaker but identity-related barriers may remain equally salient.

Ultimately, our hope is that a better understanding of what shapes training take-up can guide more effective use of public resources and support workforce adaptability in a rapidly changing economic landscape. We leave the analysis of the determinants of training decisions across different countries and occupations, and the development of a deeper understanding of the role of prospective employers in driving workers' demand for training, for future research.

References

- Daron Acemoglu and Pascual Restrepo. The race between man and machine: Implications of technology for growth, factor shares, and employment. *American economic review*, 108(6):1488–1542, 2018.
- George A. Akerlof and Rachel E. Kranton. Economics and identity. *The Quarterly Journal of Economics*, 115(3):715–753, 2000.
- George A Akerlof and Rachel E Kranton. Identity and schooling: Some lessons for the economics of education. *Journal of economic literature*, 40(4):1167–1201, 2002.
- Livia Alfonsi, Oriana Bandiera, Vittorio Bassi, Robin Burgess, Imran Rasul, Munshi Sulaiman, and Anna Vitali. Tackling youth unemployment: Evidence from a labor market experiment in uganda. *Econometrica*, 88(6):2369–2414, 2020.
- Steffen Altmann, Armin Falk, Simon Jäger, and Florian Zimmermann. Learning about job search: A field experiment with job seekers in germany. *Journal of Public Economics*, 164:33–49, 2018.
- ANPAL. Nota gol n. 1/2024 - focus anpal n. 171: Dati al 31 gennaio 2024. Technical report, ANPAL, Agenzia Nazionale Politiche del Lavoro, 2024. URL https://storicoanpal.politicheattive.lavoro.gov.it/documents/552016/1309678/Nota%2bGOL%2bn_1_2024_Focus%2bAnpal%2bn_171_dati%2bal%2b31g/Nota%20GOL%20n_1_2024_Focus%20Anpal%20n_171_dati%20al%2031gennaio2024382c.pdf?t=1709209718262.
- Erhan Artuç, Shubham Chaudhuri, and John McLaren. Trade shocks and labor adjustment: A structural empirical approach. *American economic review*, 100(3):1008–1045, 2010.
- Orazio Attanasio, Adriana Kugler, and Costas Meghir. Subsidizing vocational training for disadvantaged youth in colombia: Evidence from a randomized trial. *American Economic Journal: Applied Economics*, 3(3):188–220, 2011.
- David H Autor, David Dorn, and Gordon H Hanson. The china syndrome: Local labor market effects of import competition in the united states. *American economic review*, 103(6):2121–2168, 2013.
- Andrea Bassanini and Wooseok Ok. How do firms’ and individuals’ incentives to invest in human capital vary across groups? 2004.
- Martina Bazzoli, Gianni De Fraja, Silvia De Poli, Enrico Rettore, and Antonio Schizzerotto. Skills training programmes for unemployed workers in developed economies. *LABOUR*, 2026.
- Luc Behaghel, Sofia Dromundo Mokrani, Marc Gurgand, Yagan Hazard, and Thomas Zuber. Encouraging and directing job search: Direct and spillover effects in a large scale experiment. 2022.
- Michele Belot, Philipp Kircher, and Paul Muller. Providing advice to jobseekers at low cost: An experimental study on online advice. *The review of economic studies*, 86(4):1411–1447, 2019.
- Michele Belot, Bart K de Koning, Didier Fouarge, Philipp Kircher, Paul Muller, and Sandra Phlippen. Advising job seekers in occupations with poor prospects: A field experiment. *NBER WP 33819*, 2024.
- Yoram Ben-Porath. The production of human capital and the life cycle of earnings. *Journal of political economy*, 75(4, Part 1):352–365, 1967.
- Apurav Yash Bhatiya, Bhaskar Chakravorty, Clément Imbert, and Roland Rathelot. How do beliefs and preferences over jobs affect enrollment in vocational training: Experimental evidence from india. 2024.
- Tito Boeri and Pietro Garibaldi. Shadow activity and unemployment in a depressed labour market. *Available at SSRN 323388*, 2002.
- Hanna Brosch, Philipp Lergetporer, and Florian Schoner. Worker beliefs about firm training. 2025.
- Mirjam Bächli, Rafael Lalive, and Michele Pellizzari. Helping Jobseekers with Recommendations Based on Skill Profiles or Past Experience: Evidence from a Randomized Intervention. IZA Discussion Papers 17713, Institute of Labor Economics (IZA), February 2025. URL <https://ideas.repec.org/p/iza/izadps/dp17713.html>.

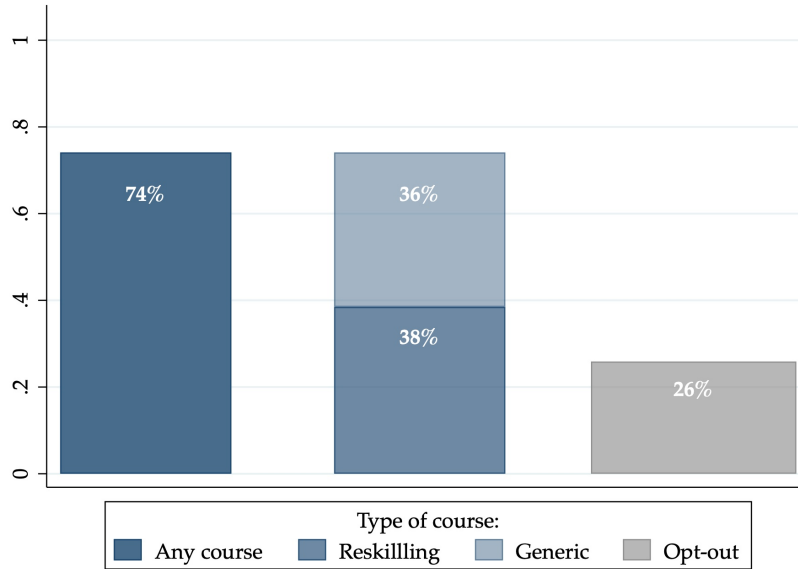
- Emile Cammeraat and Mariagrazia Squicciarini. Burning glass technologies' data use in policy-relevant analysis: An occupation-level assessment. 2021.
- David Card, Jochen Kluge, and Andrea Weber. What works? a meta analysis of recent active labor market program evaluations. *Journal of the European Economic Association*, 16(3):894–931, 2018. doi: 10.1093/jeea/jvx028.
- Fredrik Carlsson and Peter Martinsson. Design techniques for stated preference methods in health economics. *Health economics*, 12(4):281–294, 2003.
- Carlos Carrillo-Tudela and Ludo Visschers. Unemployment and endogenous reallocation over the business cycle. *Econometrica*, 91(3):1119–1153, 2023.
- Guilhem Cassan, Daniel Keniston, and Tatjana Kleineberg. A division of laborers: Identity and efficiency in india. Technical report, National Bureau of Economic Research, 2021.
- Bhaskar Chakravorty, Wiji Arulampalam, Apurav Yash Bhatiya, Clément Imbert, and Roland Rathelot. Can information about jobs improve the effectiveness of vocational training? experimental evidence from india. *Journal of Development Economics*, 169:103273, 2024.
- R. Dennis Cook and Christopher J. Nachtsheim. A comparison of algorithms for constructing exact d-optimal designs. *Technometrics*, 22(3):315–324, 1980.
- Bruno Crépon and Gerard J Van Den Berg. Active labor market policies. *Annual Review of Economics*, 8: 521–546, 2016.
- Alexia Delfino. Breaking gender barriers: Experimental evidence on men in pink-collar jobs. *American Economic Review*, 114(6):1816–1853, 2024.
- Stefano DellaVigna, Jörg Heining, Johannes F Schmieder, and Simon Trenkle. Evidence on job search models from a survey of unemployed workers in germany. *The Quarterly Journal of Economics*, 137(2): 1181–1232, 2022.
- Eurostat. Statistics on young people neither in employment nor in education or training, 2022. URL https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Statistics_on_young_people_neither_in_employment_nor_in_education_or_training.
- Priscilla Fialho, Glenda Quintini, and Marieke Vandeweyer. Returns to different forms of job related training: Factoring in informal learning. 2019.
- Paula Garda. Enhancing employability and skills to meet labour market needs in italy. (1401), 2017.
- Daniel Goller, Martin Harrer, Michael Lechner, and Joachim Wolff. Active labour market policies for the long-term unemployed: New evidence from causal machine learning. *IZA Discussion Paper No. 14450*, 2021. URL <https://arxiv.org/abs/2106.10141>.
- Dominique Goux, Marc Gurgand, and Eric Maurin. Adjusting your dreams? the effect of school and peers on dropout behaviour. 2014.
- L. Guiso, H. Herrera, M. Morelli, and T. Sonno. Economic insecurity and the demand for populism in europe. *Economica*, 91(362):588–620, 2024. doi: <https://doi.org/10.1111/ecca.12513>. URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/ecca.12513>.
- Brad Hershbein and Lisa B Kahn. Do recessions accelerate routine-biased technological change? evidence from vacancy postings. *American Economic Review*, 108(7):1737–1772, 2018.
- Caroline Hoxby, Sarah Turner, et al. Expanding college opportunities for high-achieving, low income students.
- Anders Humlum and Pernille Plato. Reskilling and resilience. 2025.
- Anders Humlum, Jakob R Munch, and Pernille Plato. Changing tracks: human capital investment after loss of ability. *American Economic Review*, 115(5):1520–1554, 2025.

- Piemonte IRES. L'effetto occupazionale della formazione professionale in piemonte. Technical report, Istituto per le Ricerche Economiche e Sociali del Piemonte (IRES Piemonte), 2022. URL https://www.ires.piemonte.it/pubblicazioni_ires/Placement_2022.pdf.
- Derek C Jones, Panu Kalmi, and Antti Kauhanen. The effects of general and firm-specific training on wages and performance: Evidence from banking. *Oxford economic papers*, 64(1):151–175, 2012.
- Loukas Karabarbounis and Brent Neiman. The global decline of the labor share. *The Quarterly journal of economics*, 129(1):61–103, 2014.
- Lawrence F Katz, Jonathan Roth, Richard Hendra, and Kelsey Schaberg. Why do sectoral employment programs work? lessons from workadvance. *Journal of Labor Economics*, 40(S1):S249–S291, 2022.
- Antti Kauhanen and Hanna Virtanen. Heterogeneity in labor market returns to adult education. Technical report, ETLA Working papers, 2021.
- Sari Pekkala Kerr, Tuomas Pekkarinen, Matti Sarvimäki, and Roope Uusitalo. Post-secondary education and information on labor market prospects: A randomized field experiment. *Labour Economics*, 66: 101888, 2020.
- J. Kluve. The effectiveness of european active labor market programs. *Labour Economics*, 17(6):904–918, 2010.
- Michael Lechner and Conny Wunsch. Are training programs more effective when unemployment is high? *Journal of labor economics*, 27(4):653–692, 2009.
- Elisabeth Leduc and Ilan Tojerow. Closing the mismatch: Encouraging jobseekers to reskill for shortage occupations. 2025.
- Philipp Lergetporer, Katharina Werner, and Katharina Wedel. Automatability of occupations, workers' labor-market expectations, and willingness to train. 2023.
- Peter Leung and Zhuan Pei. Further education during unemployment. *Working Paper*, 2023. URL <https://arxiv.org/abs/2312.17123>.
- John A List, Azeem M Shaikh, and Yang Xu. Multiple hypothesis testing in experimental economics. *Experimental Economics*, 22:773–793, 2019.
- Amelia Manuti, Serafina Pastore, Anna Fausta Scardigno, Maria Luisa Giancaspro, and Daniele Morciano. Formal and informal learning in the workplace: A research review. *International journal of training and development*, 19(1):1–17, 2015.
- Andreas I Mueller and Johannes Spinnewijn. Expectations data, labor market, and job search. pages 677–713. Elsevier, 2023.
- OECD. *Getting Skills Right: Italy*. OECD Publishing, Paris, 2017. doi: 10.1787/9789264278639-en. URL https://www.oecd.org/en/publications/getting-skills-right-italy_9789264278639-en.html.
- OECD. *Adult Learning in Italy: What role for Training Funds?* 2019. doi: <https://doi.org/10.1787/9789264311978-en>. URL https://www.oecd.org/content/dam/oecd/en/publications/reports/2019/03/adult-learning-in-italy_glg9f08c/9789264311978-en.pdf.
- OECD. *OECD Skills Outlook 2021*. 2021. doi: <https://doi.org/10.1787/0ae365b4-en>. URL https://www.oecd.org/en/publications/oecd-skills-outlook-2021_0ae365b4-en.html.
- OECD. *OECD Skills Outlook 2023*. 2023. doi: <https://doi.org/https://doi.org/10.1787/27452f29-en>. URL https://www.oecd.org/en/publications/2023/11/oecd-skills-outlook-2023_df859811.html.
- OECD. *Do Adults Have the Skills They Need to Thrive in a Changing World?* 2024. doi: <https://doi.org/10.1787/b263dc5d-en>. URL https://www.oecd.org/en/publications/do-adults-have-the-skills-they-need-to-thrive-in-a-changing-world_b263dc5d-en.html.

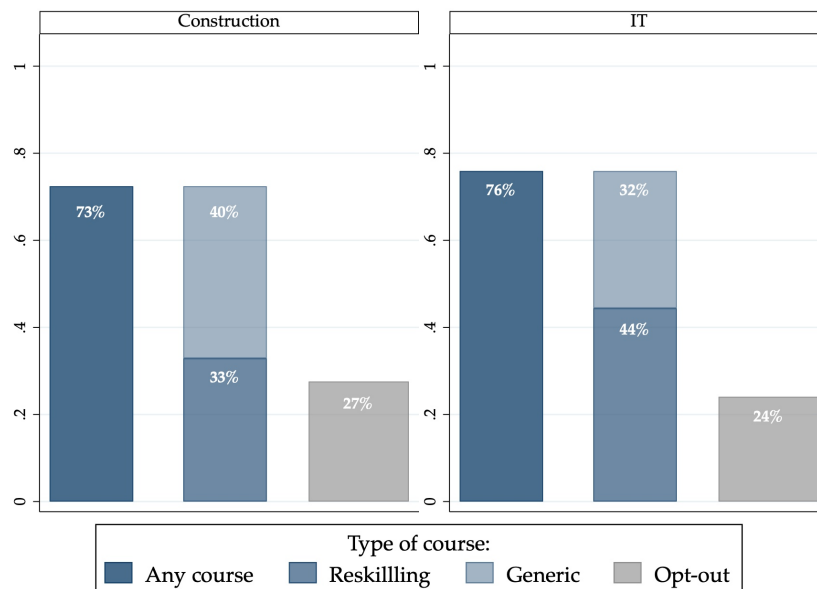
- OECD. Trends in Adult Learning. New data from the 2023 Survey of Adult Skills. Technical report, OECD Publishing, 2025.
- Suanna Oh. Does identity affect labor supply? *American Economic Review*, 113(8):2055–2083, 2023.
- Francesco Pastore and Marco Pompili. An impact assessment of ESF training courses for unemployed in the province of bolzano. *IZA Discussion Papers*, (15066), 2022. URL <https://www.iza.org/publications/dp/15066>.
- David Popp, Francesco Vona, Giovanni Marin, and Ziqiao Chen. The employment impact of green fiscal push: evidence from the american recovery act. Technical report, National Bureau of Economic Research, 2020.
- Andrew Donald Roy. Some thoughts on the distribution of earnings. *Oxford economic papers*, 3(2):135–146, 1951.
- Peter Z Schochet. *National Job Corps Study: The impacts of Job Corps on participants’ employment and related outcomes*. US Department of Labor, Employment and Training Administration, Office of . . . , 2001.
- Moses Shayo. Social identity and economic policy. *Annual Review of Economics*, 12(1):355–389, 2020.
- Jesper Strandberg and Per-Erik Josephson. What do construction workers do? direct observations in housing projects. pages 184–193, 2005.
- Kenneth E Train. *Discrete choice methods with simulation*. Cambridge university press, 2009.
- Alexandra Tsvetkova, Elettra D’Amico, Alexander Lembcke, Polina Knutsson, and Wessel Vermeulen. How well do online job postings match national sources in large english speaking countries?: Benchmarking lightcast data against statistical sources across regions, sectors and occupations. 2024.
- Theresa M Welbourne and Ted A Paterson. Advancing a richer view of identity at work: The role-based identity scale. *Personnel Psychology*, 70(2):315–356, 2017.
- World Economic Forum. The future of jobs report 2020. Report, World Economic Forum, 2020. URL https://www3.weforum.org/docs/WEF_Future_of_Jobs_2020.pdf. Published October 20, 2020.
- Giulio Zanella and Riccardo Salomone. Incentive-based active labor market programs: Insights from policy experimentation in italy. *Labour Economics*, page 102687, 2025.
- Klaus Zwerina, Joel Huber, and Warren F Kuhfeld. A general method for constructing efficient choice designs. *Durham, NC: Fuqua School of Business, Duke University*, 7, 1996.

9 Figures

Figure 1: Choice of different types of courses



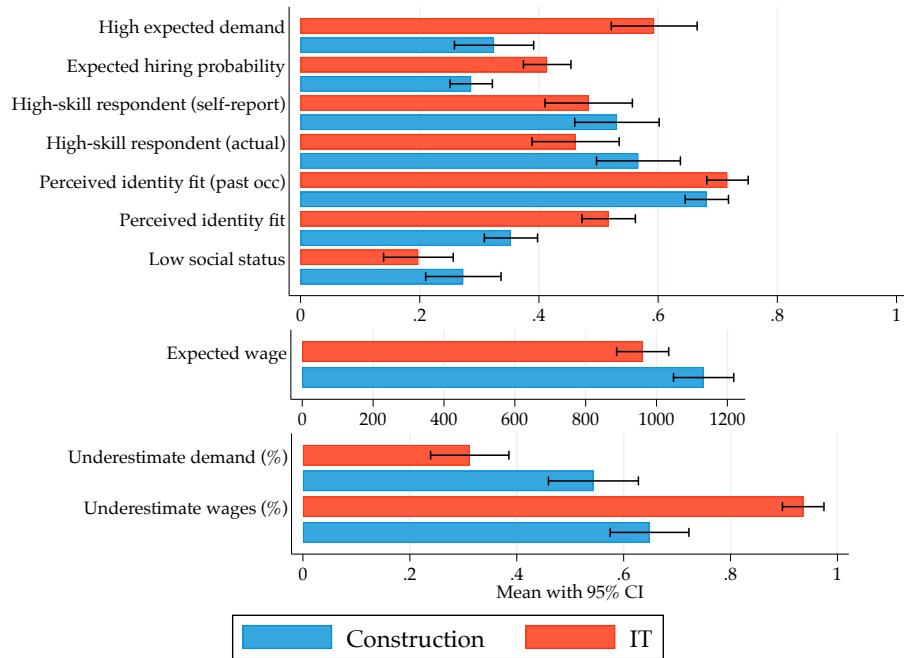
(a) Pooling treatment occupations



(b) By treatment occupation

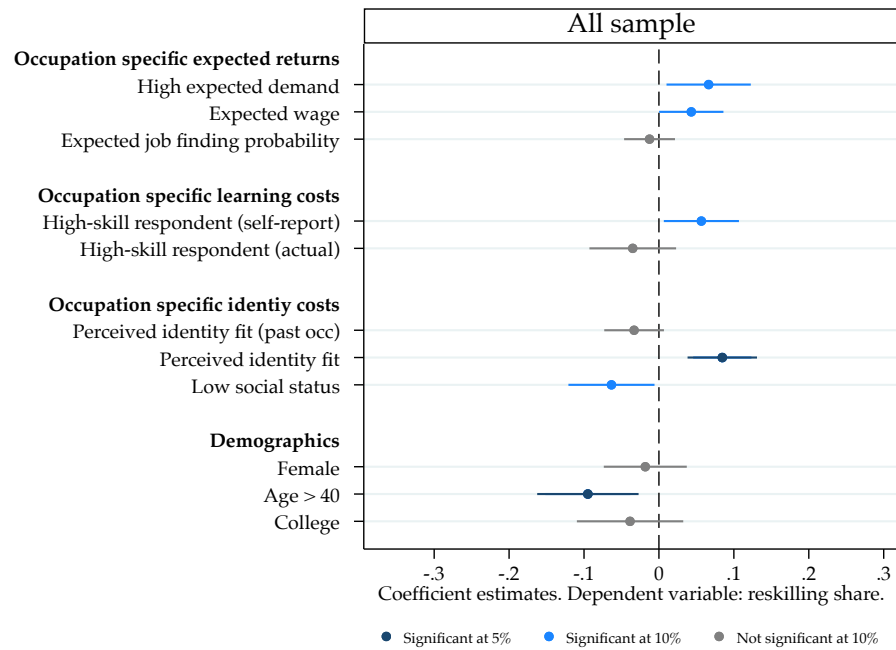
Note: the figures show how many times (out of 6) respondents chose a training course (first bar), reskilling vs generic training (second bar), or the opt-out option (third bar).

Figure 2: Expectations about the two treatment occupations

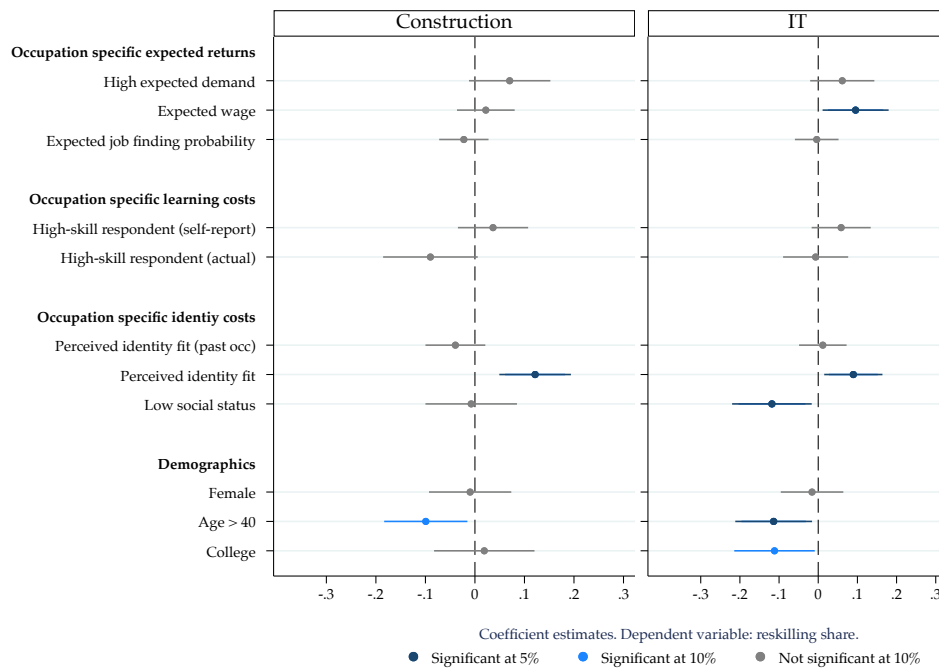


Note: The figure shows expectations and beliefs about the two treatment occupations. “High expected demand” is an indicator variable for reporting that demand from employers for the treatment occupation is high or very high. “Expected hiring probability” is the reported chances of being hired for the job within the next 3 months. The two variables labeled “High-skill respondent” are indicators for having an above average share of skills for the treatment occupation, either from actual data (“actual”) or self-reported in a checklist (“self-report”) “Perceived identity fit” is the reported fit between the treatment occupation and the respondent’s self-concept and identity. “Perceived identity fit (past occ)” is an index indicating how much the respondent felt that their main past job was part of their identity. “Low social status” is an indicator for agreeing that the treatment occupation is associated with a lower social class. Underestimate wage or demand show the share of respondent that underestimate wage and labor demand in the treatment occupation. Additional details and questions are in Table A6.

Figure 3: Individual correlates of reskilling intentions



(a) Pooling treatment occupations



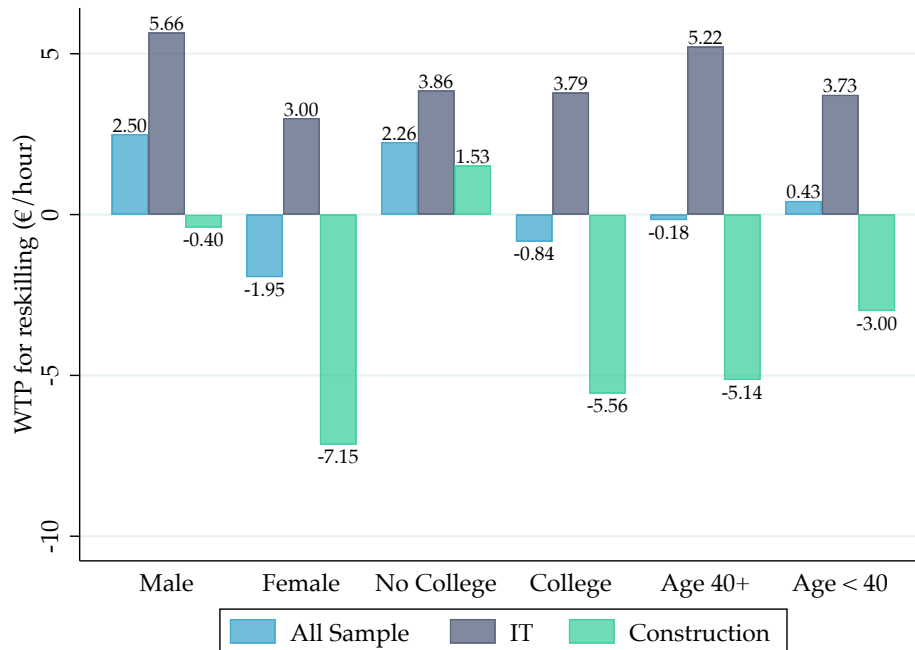
(b) By treatment occupation

Note: The figure shows the coefficients of an OLS regression of reskilling frequency on all the displayed variables. The regression also controls for the region of residence, length of unemployment, past occupation dummy, survey sample, randomization block and – in panel a – treatment occupation, as well as the additional variables shown in Appendix Figure A9a. 95% confidence intervals are shown. The estimates refer to the control group only (N=376). Table B1 provides a more detailed description of the variables used in this analysis.

Figure 4: WTP for reskilling: heterogeneity



(a) By expected returns, learning and identity costs

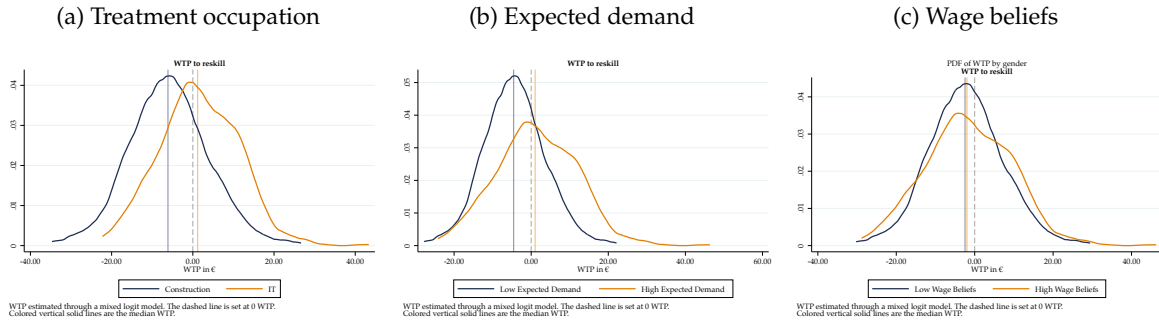


(b) By demographics

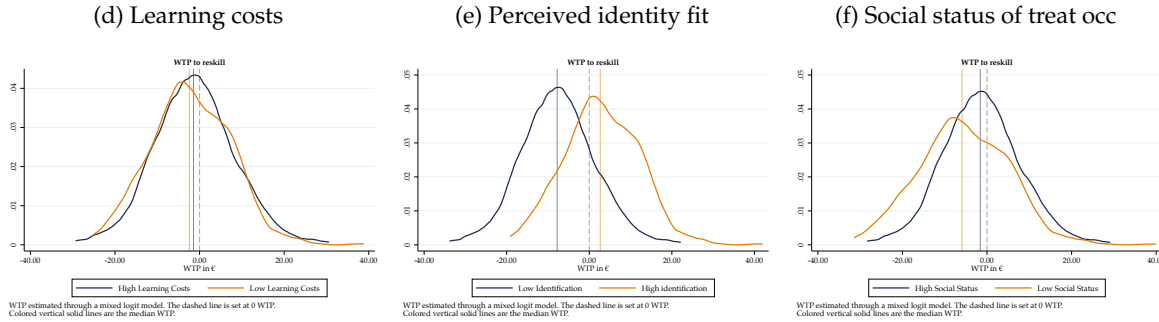
Note: The figure plots the WTP (€/hour) for reskilling in different groups of respondents. The estimates refer to the control group only (N=376). WTP are estimated through the empirical equation for WTP (Equation 5 in Section 6). Table B1 provides a more detailed description of the variables used in this analysis.

Figure 5: WTP for reskilling: distributions and heterogeneity

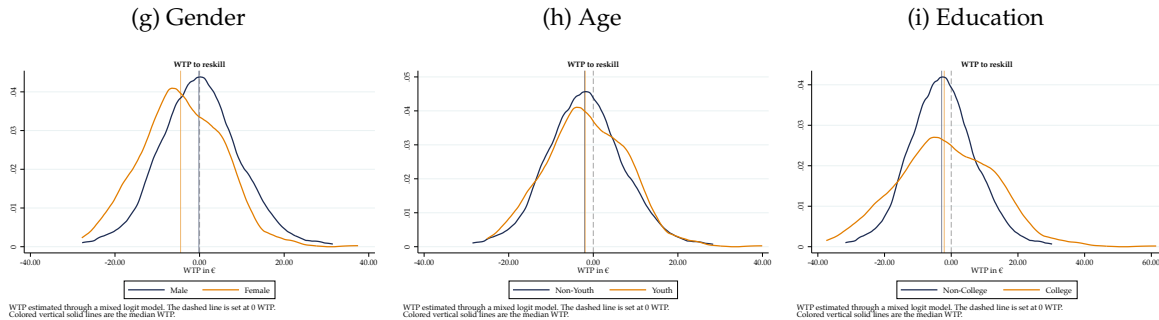
1. By treatment occupation and expected returns



2. By learning costs and identity fit

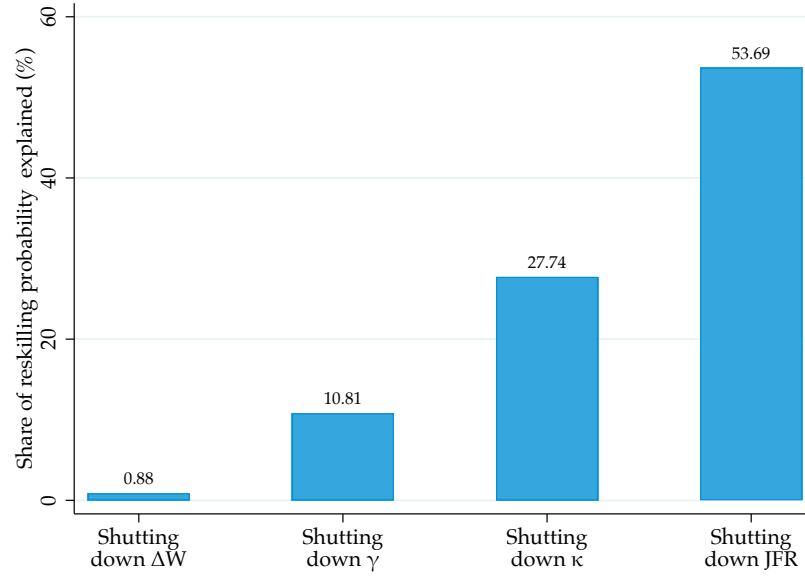


3. By demographics

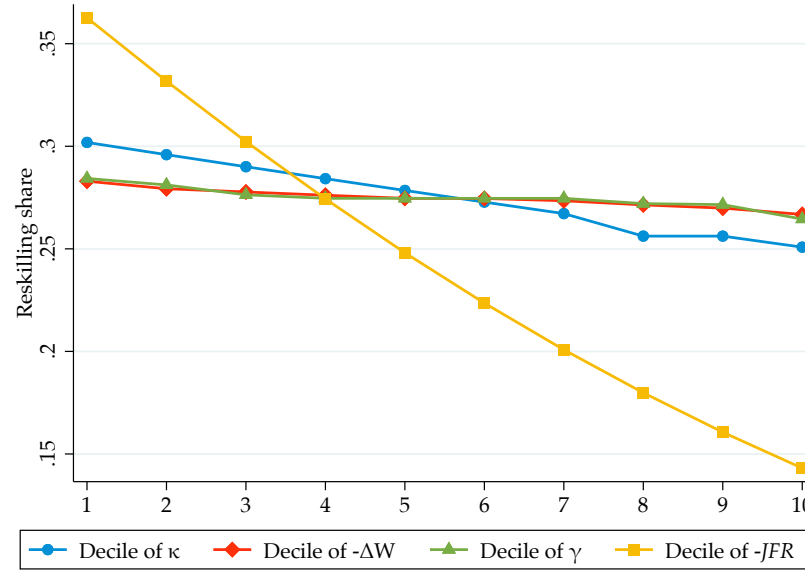


Note: The figure plots the distribution in WTP (€/hour) for reskilling in different groups of respondents. The estimates refer to the control group only (N=376). WTP are estimated through a mixed-logit model. Table B1 provides a more detailed description of the variables used in this analysis.

Figure 6: Predicted reskilling market shares: counterfactual exercises



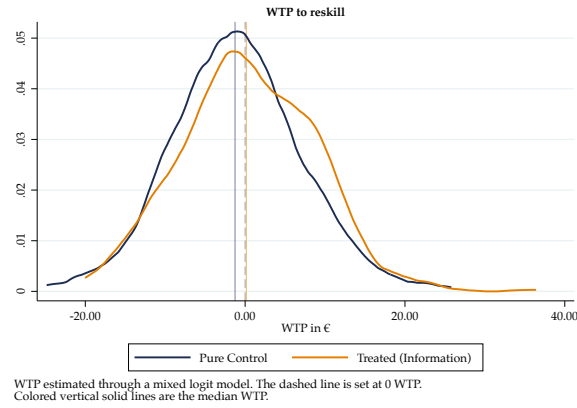
(a) % of reskilling market share explained by structural forces



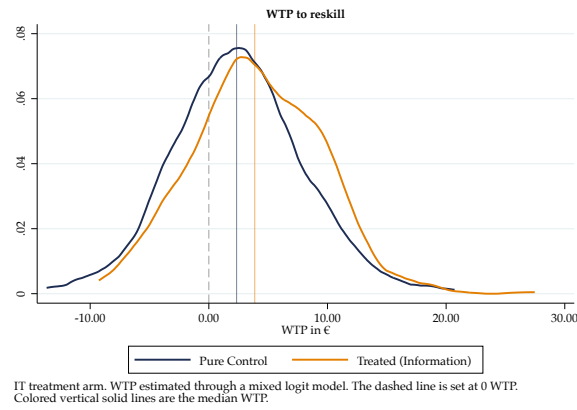
(b) Reskilling market share by decile of costs/returns

Note: The figure shows the results of two different counterfactual exercises. Figure 6a reports how much of the predicted reskilling market share (as opposed to generic training or no training) is explained by shutting down each structural force in Equation (4). ΔW measures the wage shock ($\mathbb{E}[w(r, o)] - \mathbb{E}[w(g)]$) as i) the difference between expected wage in treatment and searched occupation and ii) the difference in the expected hiring likelihood between treatment and searched occupation; γ measures learning costs as i) the actual skill ratio and ii) the perceived skill ratio; κ measures the perceived identity fit with i) the treatment occupation and ii) the main past occupation. JFR is the job finding rate probability varied in the DCE scenarios. Figure 6b plots the predicted reskilling market share across deciles of wage shocks (measured using the difference in wages between the treatment and the searched occupation), learning costs (using actual skill ratio) and identity costs (using perceived identity fit in the treatment occupation), and job finding rate. The JFR and wage shocks have been inverted, so that higher values mean lower returns.

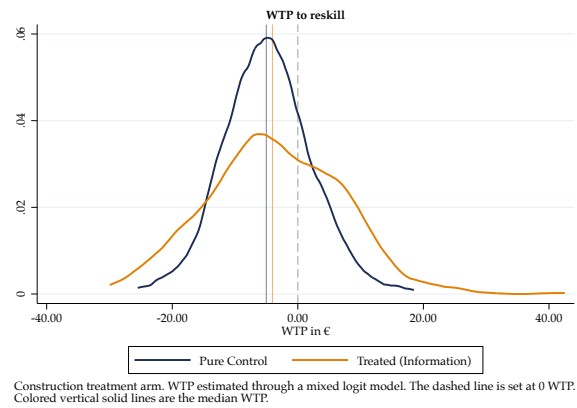
Figure 7: Information treatment effects on WTP for reskilling



(a) Pooling treatment occupations



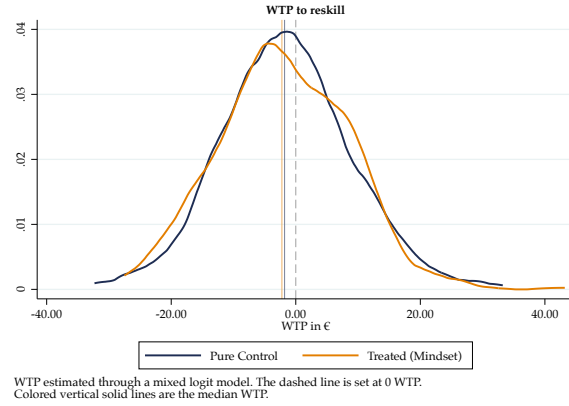
(b) IT Assistant



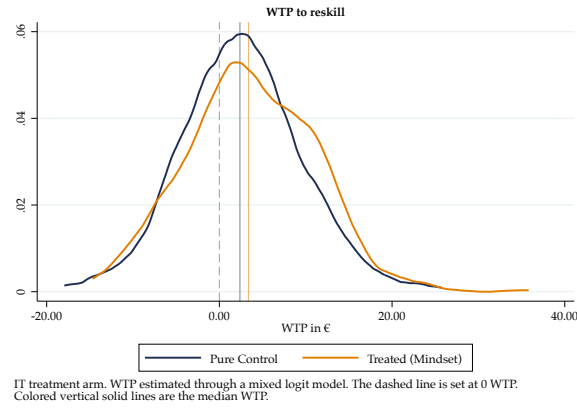
(c) Construction Technician

Note: the figures shows the distribution of WTP estimates for reskilling by treatment status, INFO vs control.

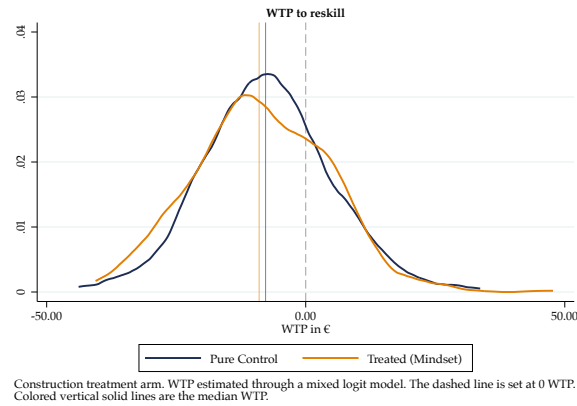
Figure 8: Mindset treatment effect on WTP for reskilling



(a) Pooling treatment occupations



(b) IT Assistant



(c) Construction Technician

Note: the figure shows the distribution of WTP estimates for reskilling by treatment status, MINDSET vs control.

10 Tables

Table 1: Marginal utilities for training features, control group

	(1) All sample	(2) Construction	(3) IT
Reskilling	0.001 (0.08)	-0.358** (0.12)	0.365*** (0.12)
Cost (€per hour)	-0.087*** (0.01)	-0.076*** (0.02)	-0.107*** (0.02)
Job Finding Rate (%)	0.013*** (0.00)	0.012*** (0.00)	0.015*** (0.00)
Duration (hours)	-0.001*** (0.00)	-0.000** (0.00)	-0.001*** (0.00)
Timing (1 if modular)	0.018 (0.05)	-0.053 (0.07)	0.103 (0.07)
Delivery (1 if online)	-0.152*** (0.05)	-0.044 (0.07)	-0.276*** (0.08)
Opt-Out	-0.194 (0.15)	-0.583*** (0.21)	0.267 (0.22)
Constant	0.484 (.62)	1.35 (01.0)	0.189 (0.84)
Controls	Yes	Yes	Yes
N	6768	3492	3276
Pseudo R-squared	0.023	0.015	0.039

Note: Standard errors in parenthesis for the logit model. Control group only * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: WTP by treatment occupation

	(1) All sample	(2) Construction	(3) IT
Reskilling	.008 [-2.137, 1.959]	-5.313 [-11.194, -1.386]	3.541 [1.230, 6.833]
Job finding rate (%)	1.597 [1.077, 2.297]	1.901 [.929, 3.397]	1.528 [.925, 2.477]
Duration (hours)	-.574 [-.921, -.293]	-.574 [-1.272, -.070]	-.592 [-1.093, -.261]
Timing (1 if modular)	.235 [-.746, 1.326]	-.766 [-2.698, 1.097]	1.062 [-.190, 2.618]
Delivery (1 if online)	-1.833 [-3.438, -.575]	-.762 [-3.037, 1.069]	-2.717 [-5.059, -.970]
Controls	Yes	Yes	Yes
N	376	194	182

Note: WTPs are the bootstrapped means of the ratio of attribute-to-cost coefficients computed from the same model of Table 1. Bootstrapped 90% CI in squared brackets. Job finding rate: WTP for and increase in 10 pp. Duration: WTP for an increase in duration of 40 hours. Control group only.

Table 3: Light-touch randomized treatments: effects on reskilling intentions

	All	IT	Construction	Incl 10-90 p	Watched all	Wrong answer FE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: DV = Choice of reskilling						
Information Treat	0.044** (0.020)	0.053* (0.028)	0.035 (0.028)	0.048** (0.020)	0.049** (0.021)	0.056** (0.024)
Mindset Treat	0.003 (0.020)	0.007 (0.029)	0.001 (0.028)	0.022 (0.022)	0.017 (0.022)	0.005 (0.021)
Mean DV	0.400	0.452	0.350	0.406	0.406	0.400
Panel B: DV = Choice of any course						
Information Treat	-0.006 (0.023)	0.022 (0.031)	-0.031 (0.034)	-0.006 (0.024)	-0.001 (0.025)	-0.016 (0.028)
Mindset Treat	-0.008 (0.023)	-0.035 (0.032)	0.027 (0.032)	-0.002 (0.024)	0.006 (0.024)	-0.010 (0.023)
Mean DV	0.735	0.742	0.728	0.738	0.742	0.735
Observations	6672	3288	3384	5826	5754	6672

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports the main results on the treatment effects on the likelihood to choose reskilling (in Panel A) or to choose any training program vs the opt-out option (in Panel B). Columns (2) and (3) limit the sample to respondents assigned to the IT or Construction occupation, respectively. Columns (4) to (6) adjust the estimates to account for inattentive respondents. Column (4) limits the sample to respondents who spent on the video page a time between the 10th and the 90th percentile. Column (5) limits the sample to respondents who watched entirely the video, and Column (6) adds a control for providing a wrong answer to at least one of the understanding checks after the video. All regressions control for age, region, education, whether they are searching for their past job, having any kids, having participated in any course in the past, interest in the treatment occupation, and differences in the features of courses in the given scenario. Observations are at the individual-scenario level. Standard errors are clustered at the individual level.

Table 4: Light-touch randomized treatments: heterogeneity of effects on reskilling intentions, by wage priors and perceived identity fit

	By Wage Priors			By Perceived Identity Fit	
	(1) Prior < actual w	(2) Prior $\geq$ actual w	(3) Uncertain	(4) Above median	(5) Below median
Information Treat	0.112*** (0.03)	-0.009 (0.05)	-0.013 (0.06)	0.073** (0.03)	0.017 (0.04)
Mindset Treat	0.013 (0.03)	-0.018 (0.04)	0.013 (0.05)	-0.010 (0.03)	0.003 (0.03)
Observations	3828	1530	1314	3510	3162
Mean DV	0.43	0.40	0.33	0.49	0.30
<i>Tests of equality of coefficients</i>					
Info: (1)=(2) / (4)=(5) p			.01		.08
Info: (1)=(3) p			.003		
Mindset: (1)=(2) / (4)=(5) p			.51		.55
Mindset: (1)=(3) p			.85		

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table shows heterogeneity in treatment effects by respondents' wage priors and perceived identity fit with the treatment occupation. Columns (1) to (3) split the sample by beliefs on wages in the treatment occupation. Column (1) estimates treatment effects on respondents who underestimate the wage, Column (2) on those who are correct or overestimate the wage, and Column (3) on those who did not report any expected wage. Column (4) to (5) split the sample by perceived identity fit with the treatment job (above vs below median, respectively). All regressions control for age, region, education, whether they are searching for their past job, having any kids, having participated in any course in the past, and interest in the treatment occupation. Observations are at the individual-scenario level. Standard errors are clustered at the individual level.

Table 5: Light-touch randomized treatments: effects on real-world training and employment

	Training engagement			Employment	
	Reskilling in IT (1)	Reskilling in other occ (2)	Generic training (3)	Found job in IT (4)	Found job in other sector (5)
Post	-0.024 (0.017)	0.012 (0.027)	-0.048 (0.033)	0.012 (0.036)	0.417*** (0.066)
Post $\times$ Info	0.035* (0.020)	-0.000 (0.041)	0.059 (0.051)	0.128** (0.055)	0.048 (0.096)
Constant	0.012** (0.005)	0.029*** (0.010)	0.076*** (0.013)	0.035** (0.014)	0.153*** (0.024)
Observations	340	340	340	340	340
R-squared	0.51	0.48	0.56	0.54	0.59
Y-mean	.01	.01	.08	.04	.15

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Comparison between the Information treatment group and the pure control. Post is a dummy variable indicating the time after completion of the survey. Info is a dummy equal to one if the individual was assigned to the information treatment. All regressions include individual fixed effects and standard errors are clustered at the individual level. Y-Mean is the baseline (pre-period) mean in the outcome variable.

The outcome variables are dummies indicating whether an individual took up any a reskilling program for occupations related to IT (1), a reskilling program in any other occupation (2), a generic training (3), or whether an individual took up a job in the IT sectors (4), or in any other sector (5).

A Appendix - Additional Figures and Tables

A.1 Figures

Figure A1: Survey structure

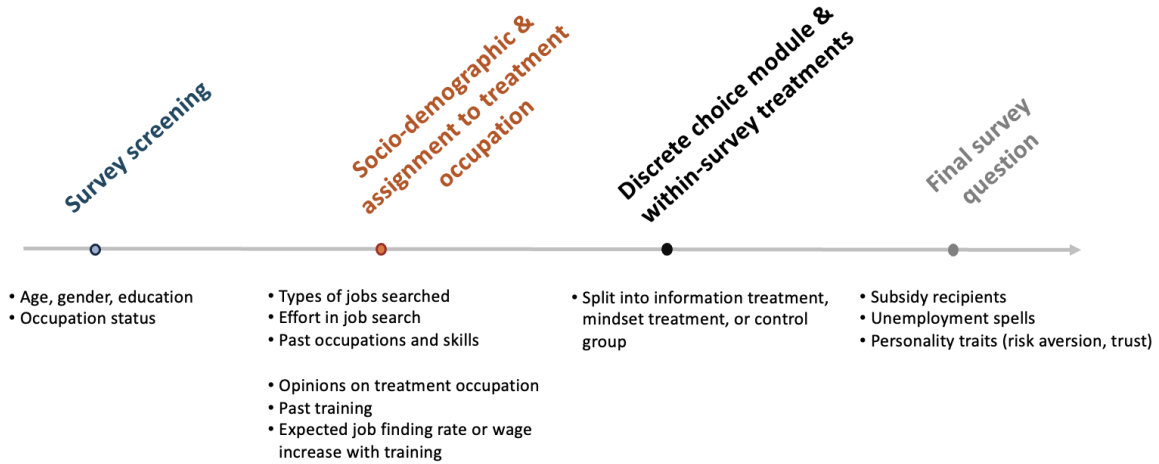


Figure A2: Illustration of the randomization process (between-subject treatments)

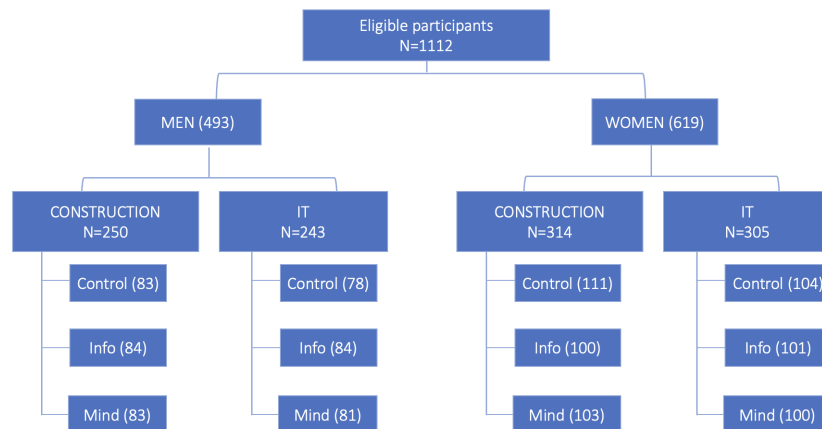
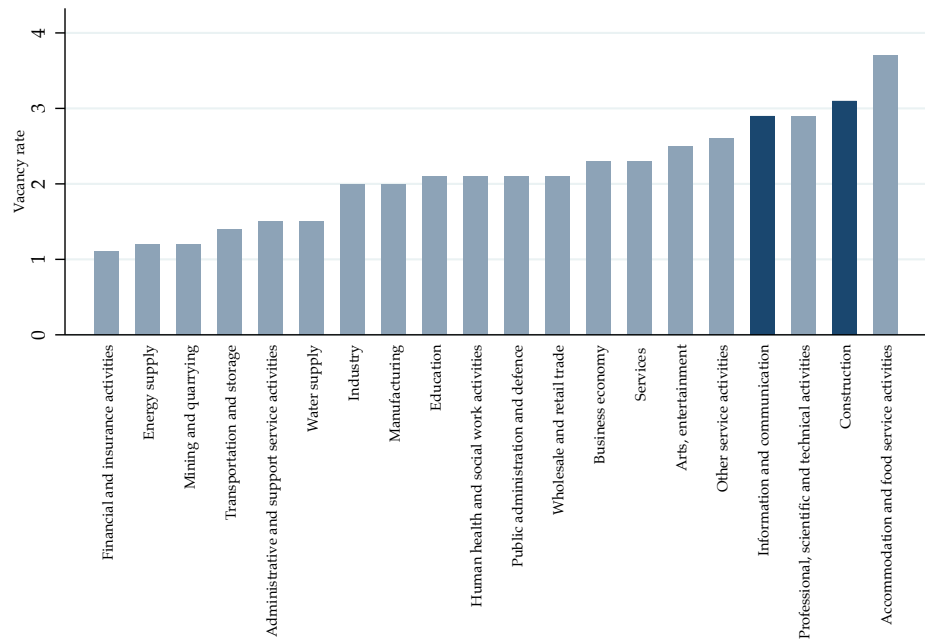
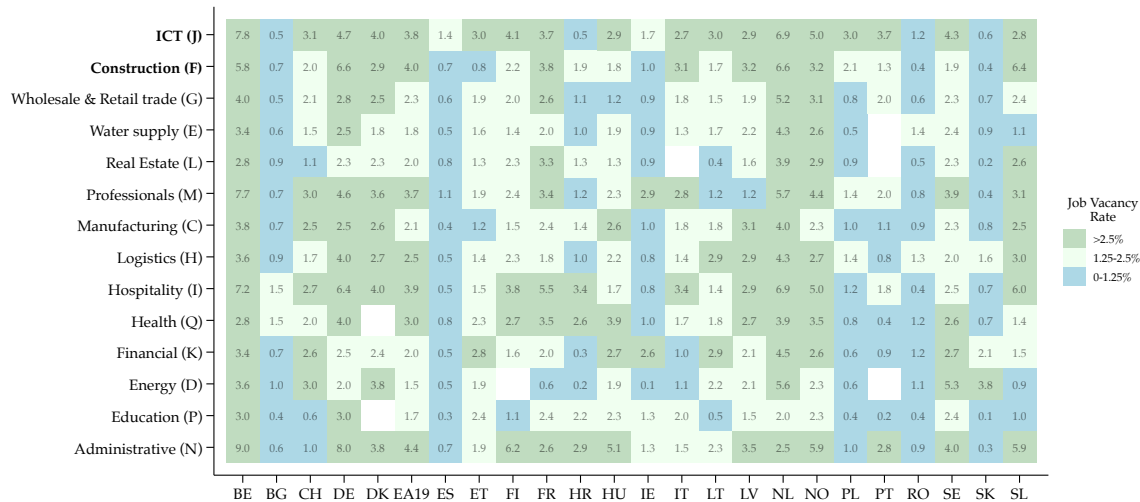


Figure A3: Vacancy rate by industry in Italy in 2023



Note: The figure shows the vacancy rate in different sectors of the Italian labor market. Source: Istat, 2023

Figure A4: Vacancy rate by industry in Europe



Note: Job vacancy rate (2021-23 average) for selected European Countries. EA19 is a composite measure of the countries in the euro area. 1-digit NACE Rev.2 industry classifier in parenthesis. Source: Eurostat, *jvs_a_rate.r2*.

Figure A5: Example of choice scenario

	Course A	Course B
Content	In Microsoft Office	For IT assistant
Price	95 € Paid by you	840 € Paid by training agency
Subsidy	Not available	80 €
Structure	Flexible: to complete over 48 weeks	Intensive: full-time for 24 weeks
Length	80 hours	500 hours
Delivery	Online	In person
Job finding rate	23%	90%

What do you choose?

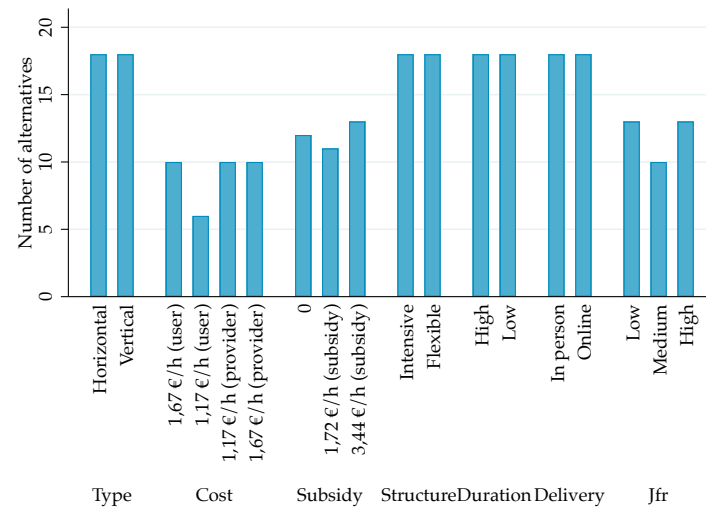
Note: the figure shows an example of a choice scenario from the discrete choice module of the survey. Each respondent saw six scenarios like this, with changing levels for each feature. The order of presentation of the different features was kept fixed for each respondent, but randomized across respondents with three possible ordering variants.

Figure A6: Discrete choice experiment (DCE): Factor levels

1	2	3	4	5	6	7
Content	Price	Subsidy	Job Finding Rate	Length	Delivery	Structure
Generic	1.67/h for trainee	1.72/h	23	80	In-Person	Intensive (Monday-Friday)
	1.17/h for trainee	3.44/h	50	200	Online	Flexible (within 48 weeks)
	1.17/h for training agency		70			
	1.67/h for training agency					
Reskilling	1.67/h for trainee	1.72/h	50	200	In-Person	Intensive (Monday-Friday)
	1.17/h for trainee	3.44/h	70	500	Online	Flexible (within 48 weeks)
	1.17/h for training agency		90			
	1.67/h for training agency					

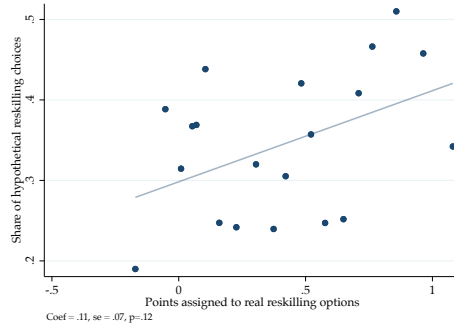
Note: The figure shows the different levels of factors used to construct training options in the discrete choice experiment.

Figure A7: Discrete choice experiment (DCE): Balance between factor levels

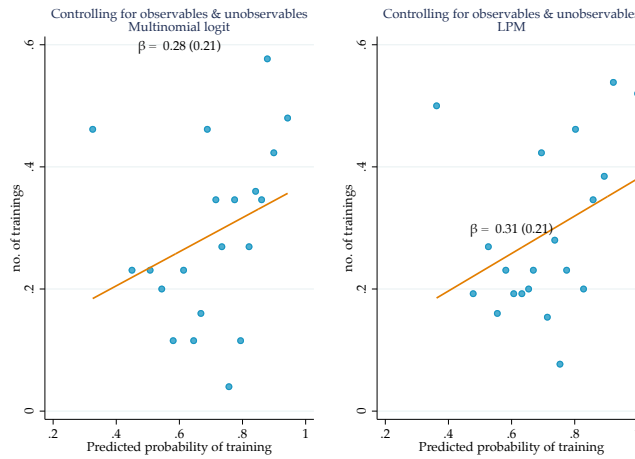


Note: The figure shows the number of course options with a given factor level. For instance, it shows that 18 courses had an online delivery and 18 courses had an in-person delivery.

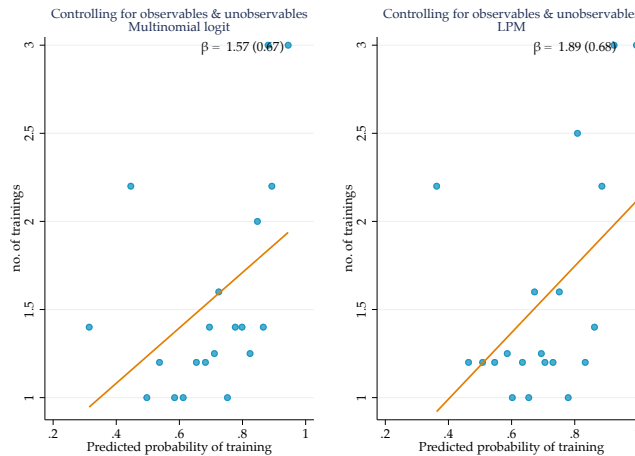
Figure A8: Survey choices and real training behavior



(a) Hypothetical choices are correlated with reskilling in an incentivized question



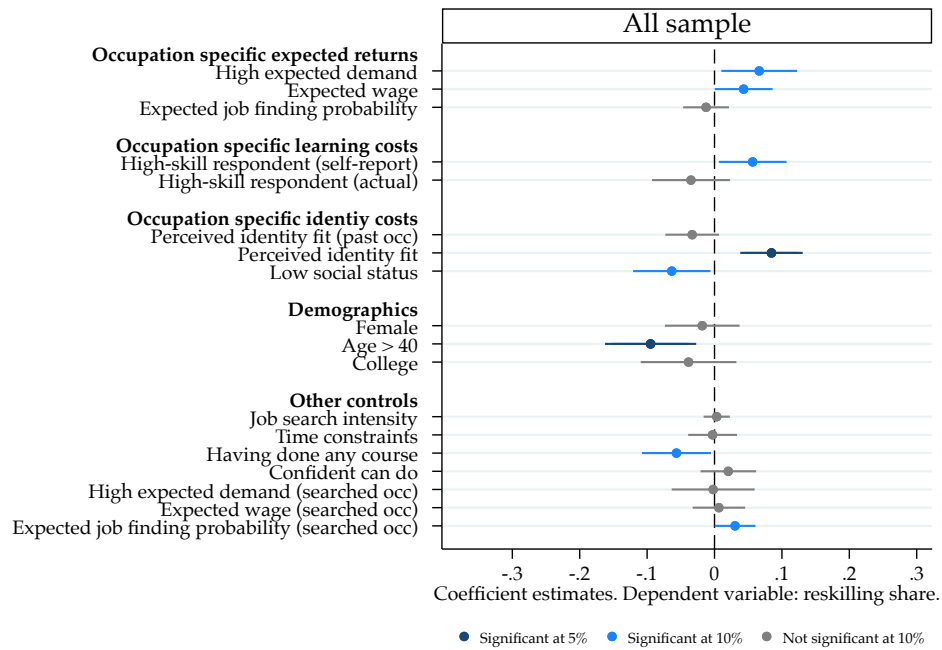
(b) Likelihood of choosing training and real behavior (extensive margin)



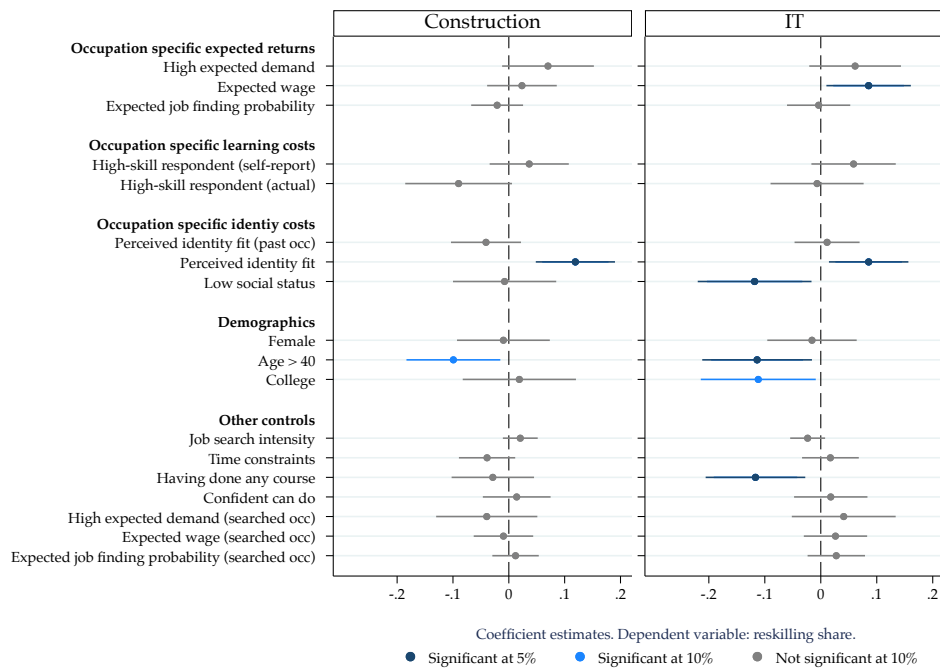
(c) Likelihood of choosing training and real behavior (intensive margin)

Note: The figure shows two exercises that correlate choices in the survey with real behavior, for the AFOL sample. Figure (a) shows that reskilling choices in the hypothetical scenarios are correlated with choices of reskilling in an incentivized question. Figure (b) shows that the predicted probability of choosing any training in the hypothetical choices in the survey is correlated with engagement in actual training courses in the last two years. The predicted probability of choosing any training uses as predictors the set of variables used for the regression models of Figure 3 and Table A7. Figure (c) shows that, for those who undertook any kind of training, the predicted probability of choosing a course in the DCE is significantly correlated with the number of training done in the last two years. We refer to this panel as the “intensive margin”, since the relation is identified only for those that have any training experience in the last two years.

Figure A9: Individual correlates of reskilling intentions



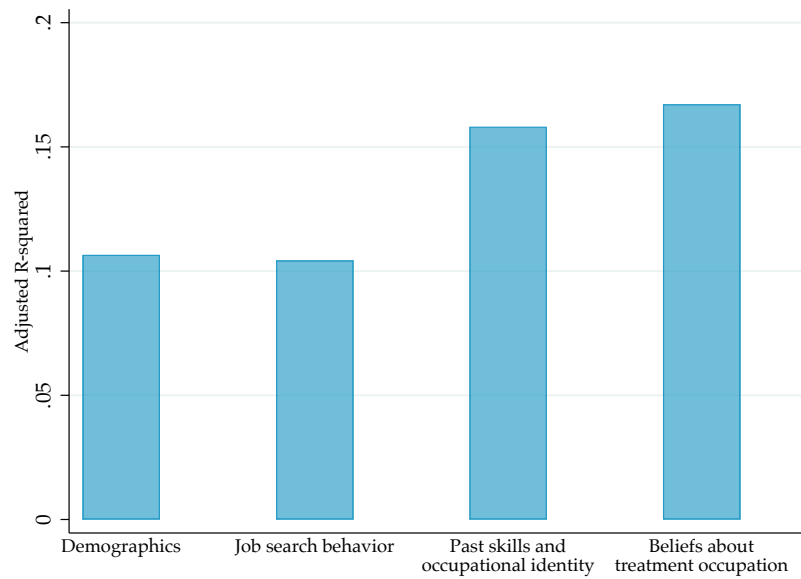
(a) Pooling treatment occupations



(b) By treatment occupation

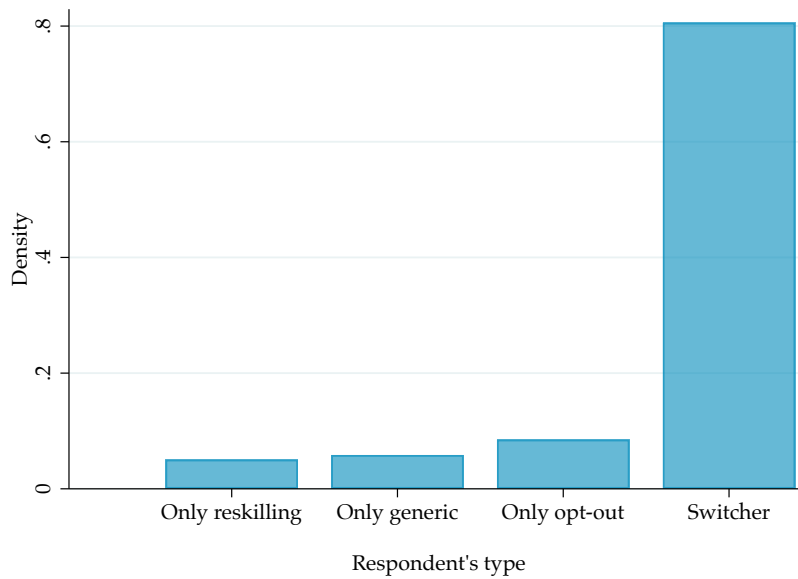
Note: The figure shows the coefficients of an OLS regression of reskilling frequency on all the displayed variables. The regression also controls for the region of residence, length of unemployment, past occupation dummy, survey sample, randomization block and – in panel a – treatment occupation. 95% confidence intervals are shown. The estimates refer to the control group only (N=376). Table B1 provides a more detailed description of the variables used in this analysis.

Figure A10: Explaining reskilling intentions with survey variables: adjusted R-squared



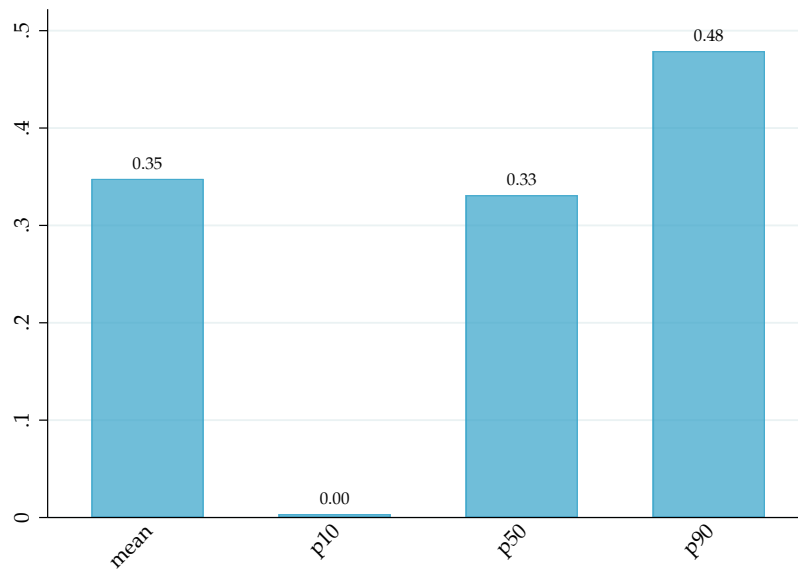
Note: The figure shows the adjusted R-squared of a regression of the frequency of reskilling choices (out of six scenarios) on the different variables used in Figures 3 and A9. The coefficients of the regression including all the controls (i.e. of the last bar in this graph) are shown in Figures 3 and A9.

Figure A11: Respondents change their choices depending on course features



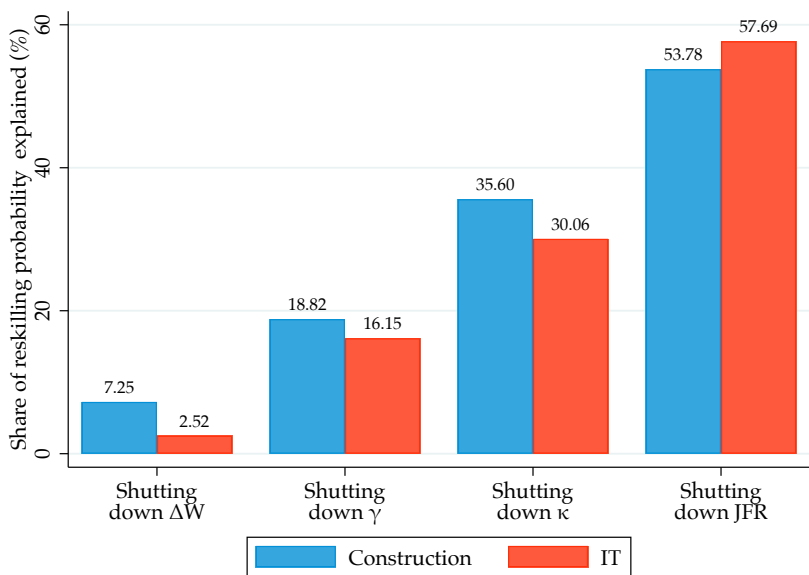
Note: the figure shows the share of respondents that always pick a certain type of training course, or always choose the opt-out, or that switch at least once between these options depending on the course features seen in the scenarios of the DCE.

Figure A12: Benchmarking the treatment effect of information on the WTP for reskilling



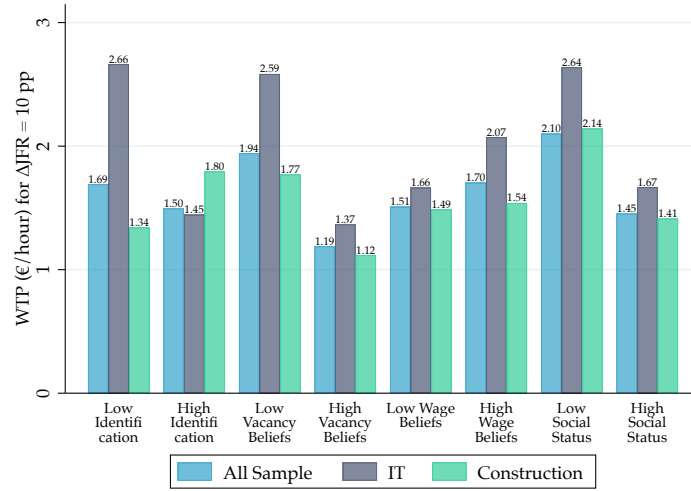
Note: the figure shows how much of the gap in willingness to pay for reskilling between female and male respondents is closed by the information treatment, at different points of the WTP distribution.

Figure A13: Predicted reskilling market shares: counterfactual exercises by treatment occupation

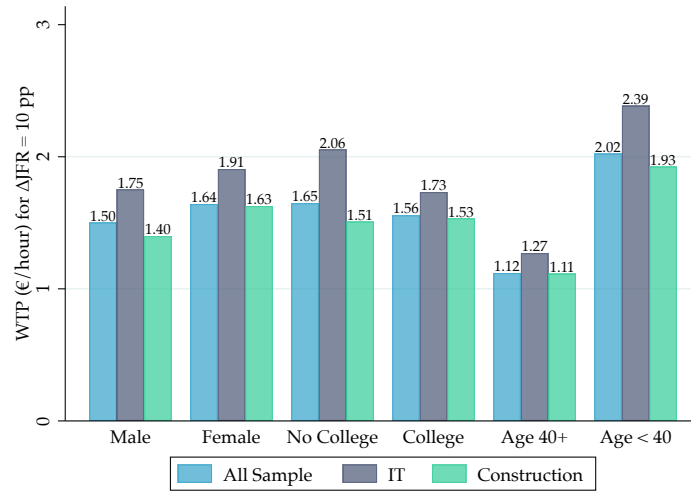


Note: The figure shows how much of the predicted reskilling market shares can be explained by shutting down each structural force in Equation (4), by treatment occupation. The description of the variables used for this exercise is reported in the note to Figure 6a.

Figure A14: WTP for Job Finding Rate: heterogeneity



(a) Heterogeneity by identity and beliefs



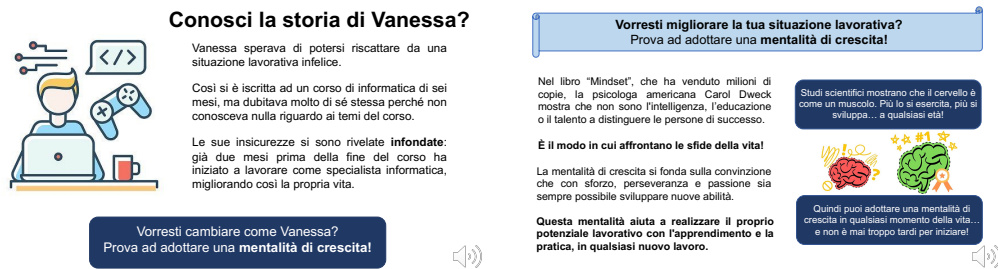
(b) Heterogeneity by demographics

Note: The figure plots the WTP (€/hour) for an increase in 10 pp of the Job Finding Rate in different groups of respondents. The estimates refer to the control group only (N=376). WTP are estimated through Equation 5. Table B1 provides a more detailed description of the variables used in this analysis.

Figure A15: Experimental treatments



(a) Information treatment (IT occupation)



(b) Mindset treatment

Note: the figure shows the main contents of the two experimental treatments. Figure (a) shows a screenshot of the information treatment video. The video showed first the information about the wage, while information about the vacancy rate appeared afterwards. For the survey company sample, we used data from Italy. For the survey with AFOL, we showed data from Lombardy only. Figure (b) shows two slides from the mindset treatment. The figure on the left describes the story of a woman who successfully changed her occupational identity after participating in training as a programmer. The figure on the right explains the concept of a growth mindset and how anyone can learn new things at any age.

A.2 Tables

Table A1: Descriptive statistics

	(1) Males	(2) Females	(3) Total
PANEL A: DEMOGRAPHICS			
Age (years)	40.44 (9.86)	40.63 (8.95)	40.55 (9.36)
Region			
North (%)	0.59 (0.49)	0.66 (0.47)	0.63 (0.48)
Centre (%)	0.10 (0.30)	0.08 (0.27)	0.09 (0.28)
South (%)	0.31 (0.46)	0.26 (0.44)	0.28 (0.45)
Has a partner (%)	0.36 (0.48)	0.58 (0.49)	0.48 (0.50)
Number of kids	0.41 (0.79)	0.77 (0.93)	0.61 (0.89)
Time spent on household chores (hours)	2.72 (1.77)	3.82 (1.85)	3.33 (1.90)
PANEL B: EDUCATION AND WORK EXPERIENCE			
Education			
Middle School	0.19 (0.40)	0.14 (0.34)	0.16 (0.37)
High School	0.55 (0.50)	0.57 (0.50)	0.56 (0.50)
College	0.25 (0.43)	0.29 (0.45)	0.27 (0.44)
Worked in the past (%)	0.91 (0.29)	0.95 (0.21)	0.93 (0.25)
Search past jobs (%)	0.52 (0.50)	0.56 (0.50)	0.54 (0.50)
Skills required for treat. occ. used in previous job (%)	0.65 (0.31)	0.71 (0.26)	0.68 (0.28)
Share of respondents in clerical or service occupations (%)	0.28 (0.45)	0.46 (0.50)	0.38 (0.49)
Share of respondents in treatment occupations (%)	0.03 (0.18)	0.01 (0.09)	0.02 (0.14)
PANEL C: UNEMPLOYMENT			
Time unemployed after studying (months)	33.13 (76.05)	27.61 (53.39)	30.06 (64.45)
Time unemployed after kids (months)	9.69 (19.35)	34.52 (53.26)	27.18 (47.27)
Lenght of unemployment (months)	40.17 (59.83)	40.32 (56.28)	40.25 (57.83)
Receives any subsidy (%)	0.42 (0.49)	0.40 (0.49)	0.41 (0.49)
Search other jobs (%)	0.70 (0.46)	0.76 (0.43)	0.73 (0.44)
Number of jobs searched	2.95 (1.77)	2.91 (1.58)	2.93 (1.66)
Willing to accept other jobs (%)	0.89 (0.32)	0.90 (0.30)	0.89 (0.31)
PANEL D: TRAINING EXPERIENCE			
Done any course (%)	0.55 (0.50)	0.55 (0.50)	0.55 (0.50)
Usefulness of course (0-10)	7.10 (2.74)	7.36 (2.73)	7.24 (2.73)
PANEL E: EXPECTATIONS ABOUT JOB SEARCH			
Expected hiring probability for searched job (0-100%)	0.43 (0.27)	0.41 (0.27)	0.42 (0.27)
Expected increment of hiring probability for searched job with course (0-100%)	0.12 (0.16)	0.13 (0.15)	0.12 (0.16)
Expected increment of hiring probability for searched job with certified course	0.07 (0.10)	0.08 (0.10)	0.08 (0.10)
Expected wage searched job (€)	1260.11 (893.35)	1075.70 (572.31)	1157.46 (737.58)
Expected wage searched job with course (€)	1267.53 (931.20)	1094.09 (617.88)	1170.98 (777.05)
Expected wage searched job with certified course (€)	1295.52 (973.79)	1121.09 (660.78)	1198.43 (818.73)
High expected demand for searched job (%)	0.41 (0.49)	0.47 (0.50)	0.44 (0.50)
Confidence in being able to do searched job (0-10)	7.54 (1.99)	7.82 (1.78)	7.69 (1.88)
Observations	493	619	1112
Standard deviation in parentheses			

Note: the table shows descriptive statistics for the sample, by gender. Variables are defined in Table B1.

Table A2: Descriptive statistics by sample and gender

	Jobcentres (AFOL) sample			Survey company sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Males	Females	Total	Males	Females	Total
PANEL A: DEMOGRAPHICS						
Age (years)	41.54 (10.55)	41.67 (9.21)	41.62 (9.73)	39.72 (9.32)	39.53 (8.54)	39.62 (8.93)
Region						
North (%)	0.99 (0.07)	0.99 (0.11)	0.99 (0.10)	0.32 (0.47)	0.31 (0.46)	0.32 (0.47)
Centre (%)	0.01 (0.07)	0.00 (0.00)	0.00 (0.04)	0.17 (0.37)	0.16 (0.37)	0.16 (0.37)
South (%)	0.00 (0.00)	0.01 (0.11)	0.01 (0.09)	0.51 (0.50)	0.53 (0.50)	0.52 (0.50)
Has a partner (%)	0.36 (0.48)	0.57 (0.50)	0.49 (0.50)	0.36 (0.48)	0.58 (0.49)	0.47 (0.50)
Number of kids	0.41 (0.77)	0.87 (0.97)	0.69 (0.92)	0.41 (0.80)	0.67 (0.88)	0.54 (0.85)
Time spent on household chores (hours)	2.77 (1.73)	3.89 (1.89)	3.47 (1.91)	2.69 (1.80)	3.74 (1.81)	3.22 (1.88)
PANEL B: EDUCATION AND WORK EXPERIENCE						
Education						
Middle School	0.22 (0.41)	0.15 (0.36)	0.18 (0.38)	0.18 (0.38)	0.12 (0.33)	0.15 (0.36)
High School	0.45 (0.50)	0.50 (0.50)	0.49 (0.50)	0.61 (0.49)	0.63 (0.48)	0.62 (0.49)
College	0.31 (0.46)	0.33 (0.47)	0.32 (0.47)	0.21 (0.41)	0.24 (0.43)	0.23 (0.42)
Worked in the past (%)	0.96 (0.19)	0.99 (0.11)	0.98 (0.14)	0.88 (0.33)	0.92 (0.28)	0.90 (0.31)
Search past jobs (%)	0.60 (0.49)	0.57 (0.50)	0.58 (0.49)	0.46 (0.50)	0.55 (0.50)	0.50 (0.50)
Skills required for treat. occ. used in previous job (%)	0.76 (0.25)	0.74 (0.24)	0.75 (0.24)	0.58 (0.32)	0.67 (0.28)	0.63 (0.30)
Share of respondents in clerical or service occupations (%)	0.26 (0.44)	0.42 (0.49)	0.36 (0.48)	0.29 (0.45)	0.51 (0.50)	0.40 (0.49)
Share of respondents in treatment occupations (%)	0.03 (0.16)	0.00 (0.06)	0.01 (0.11)	0.04 (0.20)	0.01 (0.11)	0.03 (0.16)
PANEL C: UNEMPLOYMENT						
Time unemployed after studying (months)	26.09 (87.04)	22.34 (50.06)	23.77 (66.54)	37.77 (67.58)	33.21 (56.25)	35.48 (62.14)
Time unemployed after kids (months)	4.06 (11.02)	24.77 (40.20)	19.85 (36.56)	13.94 (22.96)	47.98 (65.08)	35.62 (56.10)
Length of unemployment (months)	19.80 (47.18)	23.25 (43.03)	21.94 (44.63)	53.01 (63.39)	57.03 (62.44)	55.08 (62.87)
Receives any subsidy (%)	0.68 (0.47)	0.63 (0.48)	0.65 (0.48)	0.26 (0.44)	0.16 (0.36)	0.21 (0.40)
Search other jobs (%)	0.84 (0.37)	0.81 (0.39)	0.82 (0.39)	0.60 (0.49)	0.70 (0.46)	0.65 (0.48)
Number of jobs searched	3.27 (1.66)	3.00 (1.47)	3.10 (1.55)	2.73 (1.81)	2.83 (1.68)	2.78 (1.75)
Willing to accept other jobs (%)	0.93 (0.26)	0.88 (0.32)	0.90 (0.30)	0.86 (0.35)	0.92 (0.28)	0.89 (0.32)
PANEL D: TRAINING EXPERIENCE						
Done any course (%)	0.67 (0.47)	0.60 (0.49)	0.63 (0.48)	0.47 (0.50)	0.50 (0.50)	0.48 (0.50)
Usefulness of course (0-10)	7.19 (2.68)	7.39 (2.79)	7.31 (2.74)	7.02 (2.79)	7.31 (2.67)	7.17 (2.73)
PANEL E: EXPECTATIONS ABOUT JOB SEARCH						
Expected hiring probability for searched job (0-100%)	0.48 (0.26)	0.46 (0.27)	0.47 (0.27)	0.39 (0.27)	0.36 (0.26)	0.38 (0.26)
Expected increment of hiring probability for searched job with course (0-100%)	0.12 (0.17)	0.14 (0.17)	0.13 (0.17)	0.11 (0.15)	0.12 (0.14)	0.12 (0.15)
Expected increment of hiring probability for searched job with certified course	0.07 (0.10)	0.08 (0.11)	0.08 (0.10)	0.07 (0.10)	0.07 (0.09)	0.07 (0.09)
Expected wage searched job (€)	1509.82 (1216.13)	1152.21 (672.72)	1288.31 (933.42)	1095.32 (532.60)	994.34 (427.53)	1044.58 (484.91)
Expected wage searched job with course (€)	1464.64 (1249.49)	1160.86 (713.31)	1276.47 (963.79)	1137.45 (608.37)	1023.09 (487.97)	1079.98 (553.67)
Expected wage searched job with certified course (€)	1477.82 (1281.35)	1189.48 (757.80)	1299.21 (998.90)	1175.22 (676.77)	1048.38 (530.49)	1111.48 (610.48)
High expected demand for searched job (%)	0.56 (0.50)	0.59 (0.49)	0.58 (0.49)	0.29 (0.46)	0.35 (0.48)	0.32 (0.47)
Confidence in being able to do searched job (0-10)	7.81 (1.96)	7.77 (1.87)	7.79 (1.90)	7.39 (2.00)	7.86 (1.69)	7.61 (1.87)
Observations	196	319	515	297	300	597
sd in parentheses						

Note: The table shows descriptive statistics in the two samples of data collection, by gender.

Table A3: AFOL sample selection

	Jobcenters (AFOL) sample			Difference to Final	
	Lombardy	Initial	Final	Lombardy	Initial
Age					
18-25	17.91%	31.02%	8.35%	-9.56	-22.67
26-35	27.75%	29.09%	19.42%	-8.33	-9.68
36-45	23.02%	17.36%	29.51%	6.50	12.16
46-55	31.32%	22.53%	42.72%	11.40	20.19
Gender					
Female	54.89%	55.60%	62.70%	7.81	7.10
Male	45.11%	44.40%	37.30%	-7.81	-7.10
Education					
University degree	18.98%		32.04%	13.06	
High school diploma or equivalent	49.23%		48.54%	-0.69	
Middle school licence	31.79%		17.67%	-14.12	
Observations	17,899	44,224	512		
Education level not available for initial sample					

Note: the table shows the comparison between the overall population of unemployed registered used in the job centers of AFOL, the initial sample that got the invitation to complete the survey, and the final sample with complete responses to the survey. The Lombardy sample may differ to the “initial” invited sample because of the eligibility requirements in terms of age and Italian nationality.

Table A4: Comparison between survey samples and Italian unemployed population (from LFS, 2022)

	Survey company sample			Jobcentres sample			National		
	(1) Males	(2) Females	(3) Total	(4) Males	(5) Females	(6) Total	(7) Males	(8) Females	(9) Total
Age	39.72 (9.32)	39.53 (8.54)	39.62 (8.93)	41.54 (10.55)	41.67 (9.21)	41.62 (9.73)	31.55 (11.93)	35.97 (11.97)	34.36 (12.14)
Time since person last worked (months)	53.01 (63.39)	57.03 (62.44)	55.08 (62.87)	19.80 (47.18)	23.25 (43.03)	21.94 (44.63)	39.93 (52.42)	60.87 (45.31)	42.62 (56.86)
Inactive included							49.43 (64.03)	84.19 (95.13)	71.40 (86.66)
Years of education	13.00 (2.93)	13.44 (2.76)	13.22 (2.85)	13.41 (3.67)	13.80 (3.30)	13.65 (3.45)	11.36 (3.30)	11.57 (3.37)	11.49 (3.34)
Has a partner (%)	0.36 (0.48)	0.58 (0.49)	0.47 (0.50)	0.36 (0.48)	0.57 (0.50)	0.49 (0.50)	0.19 (0.39)	0.53 (0.0.50)	0.40 (0.49)
Has kids (%)	0.25 (0.43)	0.42 (0.49)	0.34 (0.47)	0.27 (0.44)	0.52 (0.50)	0.43 (0.49)	0.16 (0.37)	0.51 (0.50)	0.39 (0.49)
Received any subsidy (%)	0.26 (0.44)	0.16 (0.36)	0.21 (0.40)	0.68 (0.47)	0.63 (0.48)	0.65 (0.48)	0.25 (0.43)	0.22 (0.41)	0.23 (0.42)
Inactive included							0.14 (0.35)	0.11 (0.31)	0.12 (0.32)

mean coefficients; sd in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The table shows the comparison of jobseekers in our data with the Italian unemployed population according to the Labor Force Survey in Italy (2022).

Table A5: Pairwise correlation table

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) High expected demand	1.000								
(2) Expected wage	0.028	1.000							
(3) Expected job finding probability	0.038	0.053	1.000						
(4) High-skill respondent (self-report)	0.108*	0.146**	0.066	1.000					
(5) High-skill respondent (actual)	0.140*	0.173***	-0.014	0.164**	1.000				
(6) Perceived identity fit (past occ)	0.201***	0.162**	0.147**	0.127*	0.255***	1.000			
(7) Perceived identity fit	-0.030	-0.042	0.443***	-0.031	-0.078	0.143**	1.000		
(8) Low social status	0.036	0.051	0.099	0.035	0.026	0.034	0.010	1.000	
(9) Confident can do	0.061	0.019	0.538***	0.048	-0.029	0.164**	0.722***	0.024	1.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The table shows the Pearson's pairwise correlation coefficients between the main variables used in the analysis. All the variables refer to the treatment occupation, except for "Perceived identity fit (past occ)," which refers to a person's main past job.

Table A6: Expectations and beliefs about treatment occupations

Variable	All			Females			Males		
	Construction	IT	Diff	Construction	IT	Diff	Construction	IT	Diff
Perceived identity fit (0 to 10)	3.76 (3.15)	5.03 (3.14)	1.26*** (0.19)	3.30 (3.12)	4.68 (3.17)	1.38*** (0.25)	4.35 (3.09)	5.47 (3.07)	1.12*** (0.28)
Expected wage	1073.44 (669.22)	936.55 (588.87)	-136.89*** (37.84)	1012.93 (641.77)	884.69 (562.80)	-128.24*** (48.57)	1149.44 (696.05)	1001.65 (615.03)	-147.79** (59.22)
Expected wage w/ course	1161.93 (729.54)	1033.26 (627.00)	-128.68*** (40.84)	1107.12 (719.21)	992.39 (600.69)	-114.73** (53.34)	1230.78 (738.00)	1084.55 (656.19)	-146.23** (62.96)
Expected wage w/ certified course	1223.74 (801.87)	1077.07 (686.56)	-146.67*** (44.82)	1161.61 (794.71)	1030.84 (658.34)	-130.77** (58.75)	1301.78 (805.59)	1135.10 (717.59)	-166.68** (68.78)
High expected demand (%)	0.36 (0.48)	0.59 (0.49)	0.24*** (0.03)	0.34 (0.48)	0.62 (0.49)	0.28*** (0.04)	0.37 (0.48)	0.56 (0.50)	0.18*** (0.04)
Expected hiring probability (%)	31.42 (26.66)	39.79 (27.40)	8.36*** (1.62)	28.82 (26.80)	37.40 (28.05)	8.58*** (2.20)	34.70 (26.18)	42.79 (26.31)	8.09*** (2.36)
Expected hiring probability w/ course (%)	46.27 (26.70)	54.57 (25.28)	8.30*** (1.56)	45.07 (27.63)	53.77 (25.72)	8.70*** (2.15)	47.77 (25.46)	55.57 (24.74)	7.80*** (2.26)
Expected hiring probability w/ certified course (%)	53.69 (27.61)	61.57 (25.82)	7.88*** (1.60)	52.71 (28.78)	61.40 (26.32)	8.69*** (2.22)	54.91 (26.06)	61.79 (25.23)	6.88*** (2.31)
Confident can do job (0 to 10)	3.82 (3.11)	5.22 (3.10)	1.40*** (0.19)	3.39 (3.13)	4.70 (3.06)	1.32*** (0.25)	4.36 (3.01)	5.86 (3.03)	1.50*** (0.27)
Skills required for treat job used in past job (self-report, %)	0.71 (0.28)	0.66 (0.29)	-0.05*** (0.02)	0.72 (0.26)	0.70 (0.26)	-0.02 (0.02)	0.70 (0.30)	0.61 (0.31)	-0.09*** (0.03)
Treat job suits men better (%)	0.43 (0.49)	0.20 (0.40)	-0.22*** (0.03)	0.44 (0.50)	0.16 (0.36)	-0.28*** (0.04)	0.41 (0.49)	0.26 (0.44)	-0.15*** (0.04)
Treat job associated to low social class (%)	0.27 (0.45)	0.19 (0.39)	-0.08*** (0.03)	0.25 (0.43)	0.17 (0.38)	-0.07** (0.03)	0.31 (0.46)	0.22 (0.41)	-0.09** (0.04)
Observations	564	548	1,112	314	305	619	250	243	493

Standard deviations and standard errors in parentheses;

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: the table shows participants' beliefs about the treatment occupation, by gender and treatment occupation. Respondents reported their expected wage and perceived likelihood of being hired under three scenarios: (i) without taking any course, (ii) after completing a course, and (iii) after completing a course that also provides a certification. The variable "skill share for the job" is the share of skills for the treatment occupation that the respondent reports to have (asked using a checklist of skills from O*Net). See Table B1 for more details and descriptions of the variables.

Table A7: Multinomial logit: marginal effects

	Model 1		Model 2		Model 3		Model 4	
	(1) Generic training	(2) Reskilling	(3) Generic training	(4) Reskilling	(5) Generic training	(6) Reskilling	(7) Generic training	(8) Reskilling
Confidence can do treat job	0.057 (0.11)	0.390*** (0.11)	0.032 (0.11)	0.362*** (0.11)	-0.145 (0.16)	-0.000 (0.16)	-0.119 (0.17)	0.056 (0.17)
Gender	0.071 (0.22)	-0.177 (0.22)	0.001 (0.22)	-0.214 (0.22)	0.007 (0.22)	-0.132 (0.22)	-0.017 (0.23)	-0.091 (0.23)
Age > 40	-0.295 (0.21)	-0.642** (0.22)	-0.222 (0.22)	-0.587** (0.23)	-0.263 (0.23)	-0.642** (0.23)	-0.233 (0.23)	-0.635** (0.23)
More than high school	-0.214 (0.25)	-0.287 (0.26)	-0.155 (0.26)	-0.266 (0.26)	-0.119 (0.26)	-0.251 (0.26)	-0.054 (0.26)	-0.211 (0.26)
Intensity of job search	0.032 (0.07)	0.041 (0.08)	0.030 (0.07)	0.033 (0.08)	0.016 (0.08)	0.033 (0.08)	-0.002 (0.08)	0.015 (0.09)
Ever done a training course	0.244 (0.20)	-0.030 (0.20)	0.273 (0.20)	-0.017 (0.20)	0.298 (0.20)	-0.060 (0.20)	0.230 (0.20)	-0.126 (0.20)
Index of time constraints	0.037 (0.13)	0.061 (0.14)	0.079 (0.13)	0.099 (0.14)	0.024 (0.14)	0.040 (0.14)	0.012 (0.14)	-0.002 (0.14)
High exp demand for searched job			-0.036 (0.24)	0.003 (0.25)	-0.020 (0.24)	0.007 (0.25)	-0.051 (0.24)	-0.073 (0.25)
Exp wage searched job			-0.207 (0.13)	-0.065 (0.14)	-0.195 (0.12)	-0.035 (0.13)	-0.068 (0.14)	0.001 (0.15)
Exp (searched) job finding probability			0.132 (0.12)	0.184 (0.12)	0.117 (0.12)	0.186 (0.12)	0.161 (0.12)	0.244 (0.12)
High-skill respondent (self-report)					-0.159 (0.20)	0.185 (0.21)	-0.176 (0.21)	0.196 (0.21)
High-skill respondent (actual)					-0.008 (0.23)	-0.103 (0.24)	0.028 (0.25)	-0.128 (0.25)
Perc Identity fit in past job					0.174 (0.16)	-0.055 (0.16)	0.198 (0.16)	-0.034 (0.16)
Perc Identity fit treat job					0.251 (0.15)	0.533*** (0.16)	0.221 (0.15)	0.509** (0.16)
High exp demand for treat job							0.521* (0.21)	0.639** (0.22)
Exp wage treat job							-0.286 (0.21)	0.034 (0.20)
Low social status treat job							-0.283 (0.24)	-0.472 (0.24)
Exp job finding probability treat job							-0.004 (0.12)	-0.076 (0.13)
Strata controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Course features controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2256	2256	2256	2256	2256	2256	2256	2256

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The table shows estimates from a multinomial logit, where the choice of each type of course (generic vs reskilling) is compared to the choice of the opt-out. Table coefficients show marginal effects, in odd columns for the choice of generic training and in even columns for the choice of reskilling. Variables are described in Table B1.

Table A8: Test of equality between Generic Training and Reskilling in Table A7.

	Model 1	Model 2	Model 3	Model 4
Confidence	[0.000]	[0.000]	[0.188]	[0.132]
Gender	[0.131]	[0.190]	[0.395]	[0.652]
Age > 40	[0.035]	[0.028]	[0.023]	[0.015]
More than high school	[0.729]	[0.607]	[0.532]	[0.463]
Intensity of job search	[0.867]	[0.957]	[0.769]	[0.762]
Ever done a training course	[0.061]	[0.047]	[0.014]	[0.016]
Index of time constraints	[0.798]	[0.845]	[0.880]	[0.884]
High exp demand for searched job		[0.823]	[0.878]	[0.902]
Exp wage searched job		[0.194]	[0.138]	[0.539]
Exp (searched) job finding probability		[0.543]	[0.412]	[0.329]
High-skill respondent (self-report)			[0.020]	[0.012]
High-skill respondent (actual)			[0.563]	[0.343]
Perc Identity Fit past job			[0.052]	[0.046]
Perc Identity Fit treat job			[0.004]	[0.003]
High exp demand treat job				[0.462]
Exp wage treat job				[0.012]
Low social status treat job				[0.245]
Exp job finding probability treat job				[0.451]

Notes: the table reports the p-value of a standard test of equality between coefficients of the multinomial logit model. Model 1 compares coefficients between columns (1) and (2) in Table A7; Model 2 compares coefficients between columns (3) and (4); Model 3 compares coefficients between columns (5) and (6); Model 4 compares coefficients between columns (7) and (8).

Table A9: Light-touch randomized treatments: balance checks

	Control	Info	Mindset	F-test	Mindset = Info p	MHT corrected p
PANEL A: DEMOGRAPHICS						
Age (years)	40.449 (9.595)	-0.780	1.086	0.024	0.007	0.190
Region						
North (%)	0.641 (0.480)	-0.013	-0.018	0.773	0.869	0.646
Centre (%)	0.088 (0.283)	0.003	-0.000	0.980	0.857	0.936
South (%)	0.271 (0.445)	0.010	0.018	0.806	0.774	0.660
Has a partner (%)	0.469 (0.500)	0.013	0.030	0.717	0.648	0.722
Number of kids	0.604 (0.876)	-0.055	0.100	0.049	0.015	0.303
Time spent on household chores (hours)	3.343 (1.887)	-0.073	0.094	0.458	0.213	0.613
PANEL B: EDUCATION AND WORK EXPERIENCE						
Education						
Middle School	0.157 (0.364)	0.004	0.009	0.948	0.857	0.836
High School	0.612 (0.488)	-0.083	-0.079	0.034	0.907	0.026
College	0.221 (0.415)	0.077	0.075	0.025	0.962	0.023
Worked in the past (%)	0.941 (0.235)	-0.015	-0.005	0.697	0.590	0.642
Search past jobs (%)	0.571 (0.496)	-0.096	0.004	0.012	0.008	0.021
Skills required for treat. occ. used in previous job (%)	0.693 (0.268)	-0.010	-0.012	0.814	0.911	0.589
Share of respondents in clerical or service occupations (%)	0.410 (0.492)	-0.047	-0.031	0.396	0.660	0.255
Share of respondents in treatment occupations (%)	0.013 (0.115)	0.016	0.002	0.236	0.183	0.229
PANEL C: UNEMPLOYMENT						
Time unemployed after studying (months)	31.811 (73.887)	-3.319	-2.302	0.770	0.830	0.691
Time unemployed after kids (months)	24.979 (40.472)	8.616	1.061	0.239	0.170	0.455
Length of unemployment (months)	40.173 (53.909)	2.148	-1.627	0.690	0.391	0.748
Receives any subsidy (%)	0.383 (0.487)	0.039	0.045	0.314	0.854	0.282
Search other jobs (%)	0.734 (0.442)	0.003	-0.014	0.855	0.604	0.821
Number of jobs searched	2.947 (1.663)	-0.048	-0.008	0.914	0.742	0.914
Willing to accept other jobs (%)	0.910 (0.287)	-0.035	-0.013	0.296	0.338	0.227
PANEL D: TRAINING EXPERIENCE						
Done any course (%)	0.545 (0.499)	0.003	0.010	0.962	0.855	0.898
Usefulness of course (0-10)	7.380 (2.841)	-0.354	-0.051	0.372	0.266	0.323
PANEL E: EXPECTATIONS ABOUT JOB SEARCH						
Expected hiring probability for searched job (0-100%)	0.416 (0.267)	-0.012	0.019	0.278	0.112	0.576
Expected increment of hiring probability for searched job with course (0-100%)	0.130 (0.177)	-0.001	-0.017	0.241	0.153	0.208
Expected increment of hiring probability for searched job with certified course	0.073 (0.103)	0.012	-0.006	0.045	0.014	0.217
Expected wage searched job (€)	1140.681 (582.934)	-4.465	47.832	0.551	0.325	0.659
Expected wage searched job with course (€)	1161.112 (635.024)	-46.137	69.442	0.119	0.041	0.410
Expected wage searched job with certified course (€)	1196.856 (699.461)	-59.543	57.979	0.143	0.049	0.362
High expected demand for searched job (%)	0.462 (0.499)	-0.071	0.006	0.076	0.041	0.147
Confidence in being able to do searched job (0-10)	7.625 (1.897)	0.046	0.195	0.648	0.479	0.656
Observations	376	369	367			

Standard deviation in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table shows balance on observables between the three treatment groups. We run a regression of the row variable on two treatment dummies, controlling for treatment occupation and gender (stratification variables) and for the data collection sample (AFOL vs Survey Company). Columns (2) and (3) show the coefficients on the two treatment dummies, Column (4) the F-statistic for the joint significance of the two treatment dummies, Column (5) the p-value of the comparison between the two treatments, and Column (6) implements a MHT correction on p-values for the F-test as in [List et al. \(2019\)](#) (i.e. we correct the p-values for the statistical test comparing the treatment groups and the control one).

Table A10: AFOL administrative data: descriptive statistics

	All groups All periods		Control group All periods		All groups Post survey		Control group Post survey	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Reskilling (in IT)	.016	.124	.017	.13	.012	.107	.006	.076
Reskilling (other occupation)	.138	.345	.154	.362	.062	.242	.086	.281
Generic Training	.134	.341	.16	.368	.07	.255	.08	.272
Any Training	.239	.427	.263	.441	.12	.326	.143	.351
Employed in Any Sector	.685	.465	.674	.47	.571	.495	.583	.495
Employed in IT Sector	.153	.361	.16	.368	.12	.326	.126	.332
Observations	515		175		515		175	

Notes: the table reports the mean and standard deviation of employment and training take-up variables. “All groups” columns include the entire sample of respondents and “Control group” columns include only the control group. “All periods” columns include values for the periods pre- and post-survey, while “Post survey” columns include only values for the outcome after the survey.

Table A11: Light-touch randomized treatments: effects on reskilling intentions with additional controls

	All	IT	Construction	Incl 10-90 p	Watched all	Wrong ans FE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: DV = Choice of reskilling						
Information Treat	0.038* (0.020)	0.045 (0.028)	0.028 (0.029)	0.035* (0.021)	0.039* (0.021)	0.043* (0.025)
Mindset Treat	0.006 (0.021)	0.005 (0.030)	0.004 (0.028)	0.025 (0.022)	0.017 (0.022)	0.007 (0.021)
Mean DV	0.400	0.452	0.350	0.406	0.406	0.400
Panel B: DV = Choice of any course						
Information Treat	-0.010 (0.023)	0.015 (0.033)	-0.039 (0.034)	-0.012 (0.025)	-0.006 (0.025)	-0.024 (0.028)
Mindset Treat	-0.006 (0.023)	-0.039 (0.033)	0.023 (0.032)	0.001 (0.025)	0.007 (0.024)	-0.009 (0.023)
Mean DV	0.735	0.742	0.728	0.738	0.742	0.735
Observations	6672	3288	3384	5826	5754	6672

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports the main results on the treatment effects on the likelihood to choose reskilling (in Panel A) or to choose a training program vs the opt-out option (in Panel B). Columns (4) to (6) adjust the estimates to account for inattentive respondents. Column (4) limits the sample to respondents who spent on the video page a time between the 10th and the 90th percentile. Column (5) limits the sample to respondents who watched entirely the video, and Column (6) adds a control for providing a wrong answer to at least one of the understanding checks after the video. In addition to the control variables used in Tables 3 and 4, this Table controls for all the additional covariates presented in Figure 3. Standard errors are clustered at the individual level.

B Appendix - Additional details on data and measures

Additional data

We match our survey data with additional sources:

Online vacancies data from *Lightcast*. The *Lightcast* data are a tabulation of online job postings collected by the data company *Lightcast*. We have access to information on the number of job postings by year (2016-2023), region, and occupation code (4 digits ISCO). *Lightcast* strives to collect the universe of job postings and does this for several countries achieving a good representativeness in the US ([Hershbein and Kahn, 2018](#)) and in other OECD economies ([Cammaraat and Squicciarini, 2021](#); [Tsvetkova et al., 2024](#)) while also providing timely and detailed information on occupational trends. *Lightcast* conducts a set of cleaning routines to improve the statistical quality of the data with particular attention devoted to the issue of duplicate job ads. We received the data aggregated at the occupation-region-year level. We merge these occupation data with our survey responses using information on respondents' past/searched occupation and region of residence.

Administrative data on wages by occupation from *CICO*. The *CICO* (*Campione Integrato delle Comunicazioni Obbligatorie*) data are a sample of the universe of job spells in Italy. By law, upon hiring a new employee (or changing the type of contract of a current one) each employer has to notify the Italian Ministry of Labor. The sample consists of workers born on the 1st, 9th, 10th, and 11th of each month, accounting for 13 percent of all workers hired between 2010-2022. The dataset reports detailed information for each contract on start and end date, gross monthly entry wage, type of contract, and occupation among others. We exploit this data source to construct a tabulation of average gross monthly wages by occupation and year.

Matching job descriptions to occupational categories

Respondents reported their main past job in open text, including a title and a short description of key tasks. We matched these descriptions to ISCO occupational codes using a classification service offered by *Lightcast*. The matching algorithm relies on BERT-PM, a multilingual transformer model trained for paraphrase detection across languages. It computes the semantic similarity between respondents' text and official occupational titles and descriptions. Matches with a similarity score below 0.6 were manually reviewed and adjusted.

We then linked each matched occupation to its O*NET skill profile, which provides standardized information on 35 core skills, each rated from 0 to 5 in terms of level and importance. Skills rated below 2 are considered "not relevant". This linkage allows us to compute actual skill distances between respondents' past occupations and their assigned treatment occupations, and to compare these with their self-reported (perceived) skill distances elicited in the survey.

Measures of learning costs: skill distances

The following measures are used in the main analysis of the paper. They rely on the skills profile from O*NET and the mapping of occupations reported in the survey with ISCO codes (as described above):

- *Perceived* skill distance.
As part of the survey, respondents completed a skills checklist. For each treatment occupation, we presented the core skill requirements based on the O*Net classification system and asked respondents to indicate which of these skills they already possessed. The resulting share serves as a measure of *perceived* skill distance between the respondent and the treatment occupation.
- *Actual* skill distance.
We construct a measure of *actual* skill distance by comparing the respondent's most important occupation to each treatment occupation using detailed ISCO codes. We assume respondents possess all skills from their past occupation and define actual skill distance as the number of overlapping skills with the treatment occupation, divided by the total number of skills required in the treatment occupation.

Figure B1 shows that 63% of the sample report to have most of the required skills in the assigned treatment occupation. In aggregate, this is similar to the actual skill distance computed using the occupational history. However, at the individual level, 40% of jobseekers underestimate their skill distance from the treatment occupation, and 30% overestimate it by more than 10 percentage points, indicating that the actual and perceived costs of reskilling may differ (Figure B1b).

Additional measures of expected returns: beliefs vs actual returns

In the main analysis of the paper, we measure expected returns from the reskilling occupation as the difference in expected wages and hiring likelihood between the treatment and the main searched occupation, as reported by respondents in the survey.

Here we show some additional descriptive exercises that compare expectations with actual returns measured in administrative data.

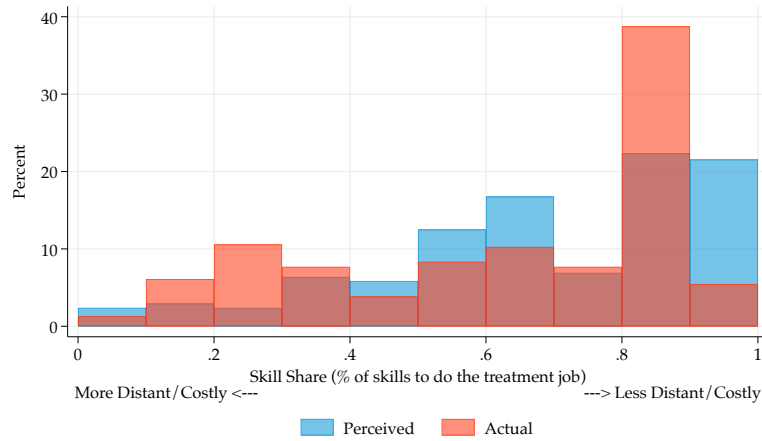
We think about “returns to reskilling” as the relative attractiveness of switching to the treatment occupation, in terms of expected wages and job-finding chances. We first construct *actual* returns using administrative data. For each respondent, we calculate the average monthly wage in the treatment occupation and their self-reported searched occupation (from CICO data). We then weight these wages by each occupation’s job vacancy share in the respondent’s region (from Lightcast data). This gives us a measure of the benefits of reskilling into the treatment occupations for jobseekers who live in the same region and search for the same preferred occupation. While we cannot tailor our measures to more detailed personal information, we expect both regional location and past experience to capture some of the key sources of variation in interpersonal returns to reskilling (Kauhanen and Virtanen, 2021).

We construct *perceived* returns similarly, but using respondents’ own beliefs. Each respondent reports their expected monthly wage and expected likelihood of being hired within 3 months in both their searched and treatment occupations. We multiply expected wages by these probabilities to create a respondent-specific expected value for each job. The log ratio between treatment and searched expected values gives us the expected return.

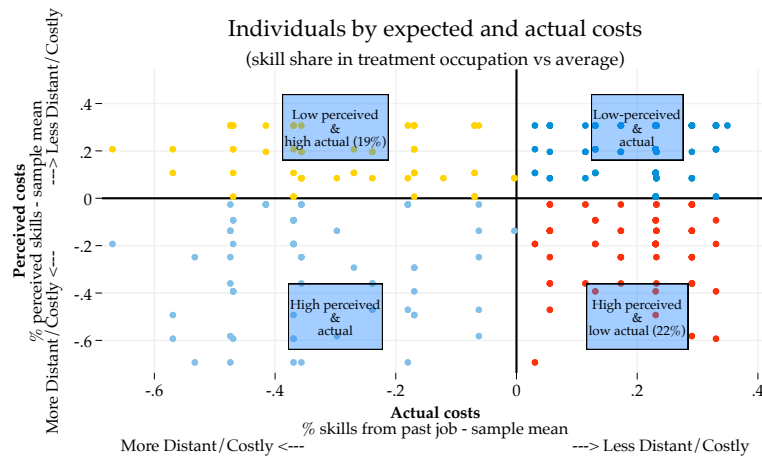
We study the joint distribution of these return metrics in Figure B2. Figure B2a shows that many respondents expect high returns: the median expected gain from switching to the treatment occupation is 440 euros/month, or 31% of the national median wage. There is also substantial variation in expectations, with the 25th percentile believing that they would lose 200 euros.

Figure B2b classifies respondents into four groups based on whether perceived and actual returns are above or below the returns in the searched occupation. For 44% of respondents, their perceptions align with the administrative data. However, 23% overestimate returns, believing reskilling is valuable when actual data suggest otherwise. Another 33% underestimate returns, perceiving a loss when they would likely benefit on average.

Figure B1: Perceived vs actual learning costs



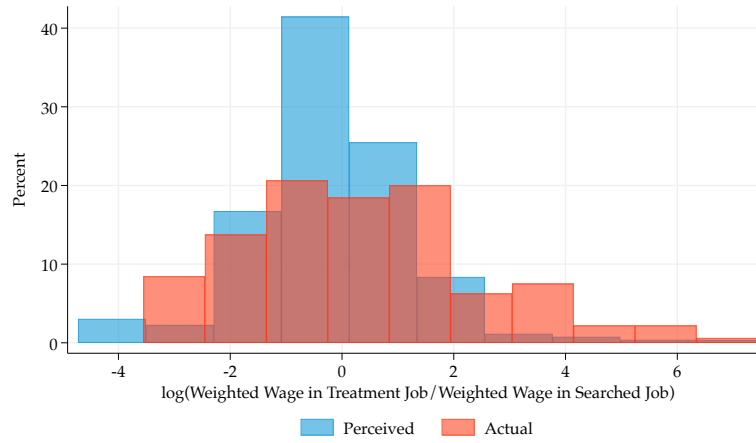
(a) Distribution of actual and perceived costs



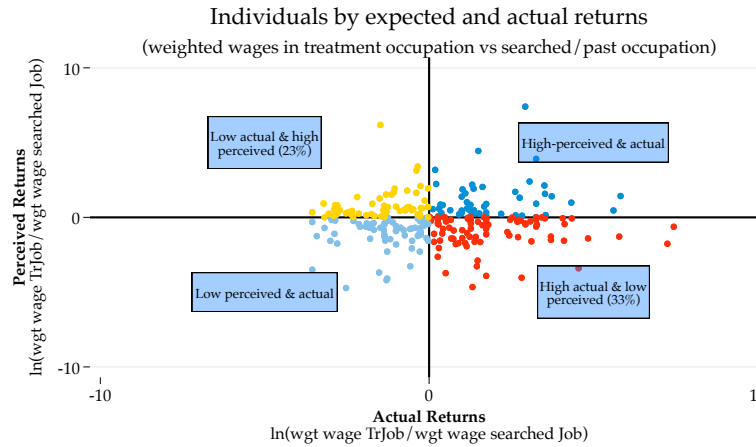
(b) Sample shares by quadrant of perceived/actual costs

Note: The figure shows the comparison between our measures of actual and perceived skill distance from the treatment occupation. "Actual costs" are constructed by linking the respondent's previous occupation (ISCO code) to its corresponding O*NET skill profile, and computing the share of overlapping skills with the treatment occupation. "Perceived costs" are based on the survey checklist in which respondents identify which of the treatment occupation's key skills (from the same O*NET skill profile) they already possess. Higher values indicate greater skill overlap, and thus lower reskilling costs.

Figure B2: Perceived vs actual returns to switching occupation



(a) Perceived vs actual returns



(b) Sample shares by quadrant of perceived/actual returns

Note: The figure shows the comparison between our measures of actual and perceived returns to switch to the treatment occupation. Panel (a) shows the distributions of actual and perceived returns. Panel (b) plots individuals by their perceived and actual returns to reskilling. Both measures are defined as log ratios relative to the respondent's searched occupation. The horizontal axis shows actual returns, computed as the log of the average wage in the treatment occupation, weighted by regional vacancy shares, divided by the average wage in the respondent's searched occupation, weighted by regional vacancy shares. The vertical axis shows perceived returns, calculated as the log of the respondent's expected wage times perceived hiring probability in the treatment occupation, divided by the same product for their searched occupation. Values above zero indicate that the treatment occupation is perceived or measured as more attractive than the searched occupation. The four quadrants classify respondents based on whether each measure is above or below zero.

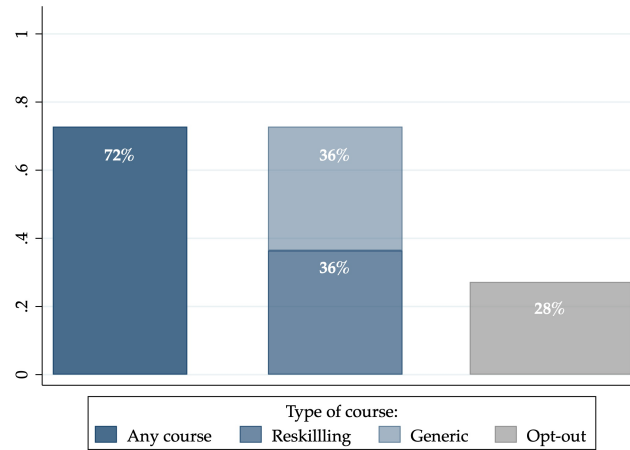
Table B1: Description of main variables and indices used in the paper

Variable	Type	Description
College	Dummy	Dummy for having completed college
Index of intensity of job search	Index	Ratio of hours spent searching to number of jobs searched, standardized
Having done any course	Dummy	Having ever participated in any training course in the past
Index of time constraints	Index	Averages and standardizes time spent on house chores and number of kids
Confidence can do treat job	Index	Confidence in doing the treatment job with current skills (scale 1-10)
High skill respondent (self-report)	Dummy	Reported share of job-specific skills for the treatment occupation from O*NET checklist above average, standardized
High skill respondent (actual)	Dummy	Actual share of job-specific skills for the treatment occupation from O*NET above average, standardized
High expected demand searched job	Dummy	Answer "High" or "Very High" to question about employers' demand in searched job (4-point scale)
High expected demand treatment job	Dummy	Answer "High" or "Very High" to question about employers' demand in treatment job
Perceived identity fit past job	Index	Standardized average agreement with four statements about past job (i.e., "I often talk about this job with family and friends", "Doing this job makes me feel proud", "This job represents me; it is part of who I am", "My family and friends identify me with this job")
Perceived identity fit treatment job	Index	Answer to the question "How well do you believe this job matches your own identity and self-perception?" (scale 1-10)
Low social status treatment job	Dummy	Agreement that the treatment job is associated with low social class
Interest in treat job	Index	Self-reported interest in treatment job (scale 1-10)
Treat job suits men better	Dummy	Agreement that treatment job is more appropriate for men
Expected wage treatment job	Continuous	Expected net monthly salary in treatment job
Expected wage treatment job w/ course	Continuous	Expected net monthly salary in treatment job after completing a training program
Expected wage treatment job w/ certification	Continuous	Expected net monthly salary in treatment job after completing a training program that gives a certification
Expected hiring probability treatment job	Percentage	Probability of being hired for the treatment job within 3 months
Expected hiring probability treatment job w/ course	Percentage	Probability of being hired for treatment job after completing a training program
Expected hiring probability treatment job w/ certification	Percentage	Probability of getting treatment job after completing a training program that gives a certification
Expected wage searched job	Continuous	Net monthly salary expected if offered the searched job
Expected wage searched job with course	Continuous	Expected net monthly salary in searched job after completing a training program
Expected wage searched job w/ certification	Continuous	Expected net monthly salary in searched job after completing a training program that gives a certification
Expected hiring probability searched job	Percentage	Probability of being hired for the searched job
Expected hiring probability searched job w/ course	Percentage	Probability of being hired for searched job after completing a training program
Expected hiring probability searched job w/ certification	Percentage	Probability of being hired for searched job after completing a training program that gives a certification

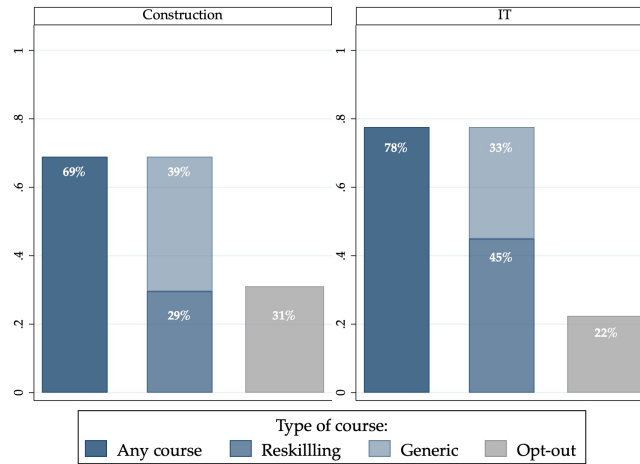
C Appendix - Weighted Results

In this section, we apply weights to improve the representativeness of our results. We construct our weights using the stock of unemployed in Italy by age bracket, education level, and gender. We obtain these population figures from the Italian National Statistical Institute (ISTAT).³⁵ Specifically, we construct analytical weights as the ratio of the number of unemployed individuals in a given demographic bin in the population to the number in the corresponding bin in our survey. The bins are defined by the intersection of gender (male, female), age group (15–34, 35–49, 50–64), and education level (lower secondary, high school, college), yielding 18 distinct categories.

Figure C1: Choice of different types of courses - weighted



(a) Pooling treatment occupations

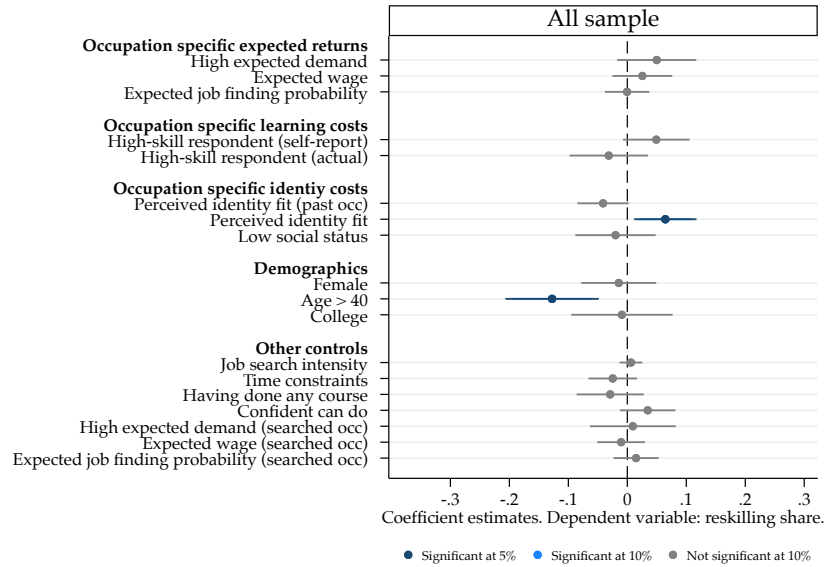


(b) By treatment occupation

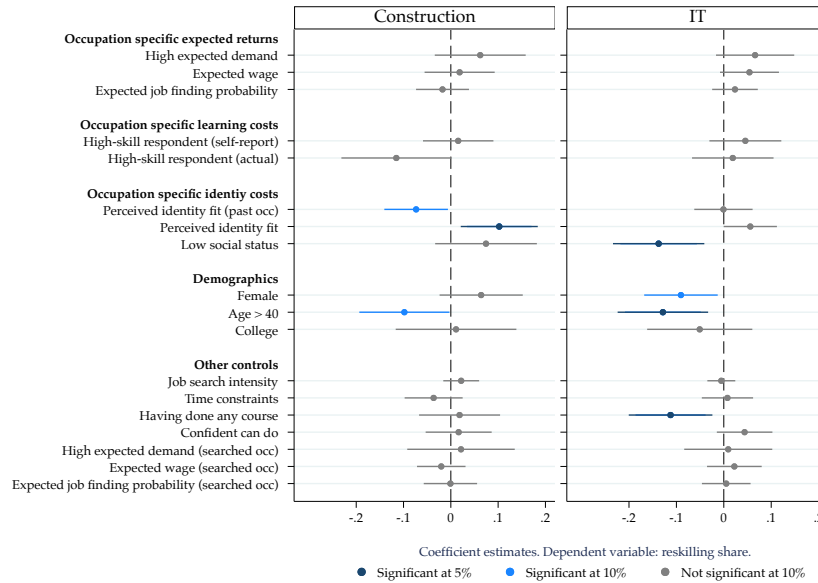
Note: the figure shows how many times (out of 6) respondents chose a training course (first bar), reskilling vs generic training (second bar), or the opt-out option (third bar).

³⁵Data are available on the ISTAT website at this link: <https://esploradati.istat.it/databrowser/>

Figure C2: Individual correlates of reskilling intentions - weighted results



(a) Pooling treatment occupations



(b) By treatment occupation

Note: The figure shows the coefficients of an OLS regression of reskilling frequency on all the displayed variables. The regression also controls for the region of residence, length of unemployment, past occupation dummy, survey sample, randomization block, and treatment occupation. 95% confidence intervals are shown. The estimates refer to the control group only (N=376). The p-value on the coefficient on perceived identity fit in IT is $p = 0.102$.

Table C1: Marginal utilities for training features, control group. Weighted estimates.

	(1) All sample	(2) Construction	(3) IT
Reskilling	−0.080 (0.11)	−0.354** (0.17)	0.267*** (0.15)
Cost (€per hour)	−0.090*** (0.02)	−0.079*** (0.02)	−0.118*** (0.03)
Job Finding Rate (%)	0.014*** (0.00)	0.010*** (0.00)	0.019*** (0.00)
Duration (hours)	−0.001*** (0.00)	−0.001** (0.00)	−0.001*** (0.00)
Timing (1 if modular)	−0.032 (0.07)	−0.162 (0.10)	0.107 (0.10)
Delivery (1 if online)	−0.101*** (0.07)	0.001 (0.10)	−0.225*** (0.10)
Opt-Out	−0.259 (0.19)	−0.617*** (0.27)	0.212 (0.30)
Constant	1.25 (.51)	1.09 (.79)	1.85 (.79)
Controls	Yes	Yes	Yes
<i>N</i>	6696	3474	3222
Pseudo R-squared	0.033	0.033	0.070

Note: Standard errors in parenthesis for the logit model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C2: WTP by treatment occupation. Weighted estimates.

	(1) All sample	(2) Construction	(3) IT
Reskilling	-.862 [-4.180, 2.170]	-5.692 [-18.808, 1.689]	2.598 [-.411, 6.709]
Job finding rate (%)	1.708 [.946, 2.891]	2.002 [.633, 5.545]	1.659 [.848, 3.319]
Duration (hours)	-.547 [-1.199, -.155]	-.815 [-2.290, .108]	-.473 [-1.133, -.073]
Timing (1 if modular)	-.147 [-1.622, 1.432]	-1.518 [-4.638, 1.713]	1.260 [-.607, 3.942]
Delivery (1 if online)	-1.311 [-3.563, .529]	-.011 [-3.134, 4.413]	-2.385 [-5.735, -.351]
Controls	Yes	Yes	Yes
N	376	194	182

Note: Bootstrap estimates and bootstrapped 90% CI in squared brackets. Job finding rate: WTP for and increase in 10 pp. Duration: WTP for an increase in duration of 40 hours.

Table C3: Light-touch randomized treatments: effects on reskilling intentions, weighted

	All	IT	Construction	Incl 10-90 p	Watched all	Wrong ans FE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: DV = Choice of reskilling						
Information Treat	0.075*** (0.025)	0.053* (0.031)	0.095*** (0.035)	0.073*** (0.025)	0.069*** (0.026)	0.067** (0.028)
Mindset Treat	-0.014 (0.025)	-0.034 (0.033)	0.014 (0.034)	-0.003 (0.028)	-0.003 (0.027)	-0.015 (0.026)
Mean DV	0.400	0.452	0.350	0.406	0.406	0.400
Panel B: DV = Choice of any course						
Information Treat	0.038 (0.028)	0.037 (0.035)	0.036 (0.041)	0.032 (0.029)	0.039 (0.030)	0.003 (0.034)
Mindset Treat	0.010 (0.030)	-0.067* (0.038)	0.090** (0.039)	0.013 (0.031)	0.026 (0.032)	0.002 (0.030)
Mean DV	0.736	0.743	0.729	0.738	0.743	0.736
Observations	6606	3234	3372	5766	5706	6606

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports the main results on the treatment effects on the likelihood to choose reskilling (in Panel A) or to choose a training program vs the outside option (in Panel B). Controls and sample restrictions are the same as in Table 3. Columns (4) to (6) adjust the estimates to account for inattentive respondents. Column (4) limits the sample to respondents who spent on the video page a time between the 10th and the 90th percentile. Column (5) limits the sample to respondents who watched entirely the video, and Column (6) adds a control for providing a wrong answer to at least one of the understanding checks after the video. Standard errors are clustered at the individual level.