Unwilling to reskill? Evidence from a survey experiment with jobseekers*

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Abstract

We study demand-side barriers preventing jobseekers from pursuing reskilling in high-demand occupations. By means of a discrete choice experiment, we quantify the demand for reskilling among Italian jobseekers in two high-demand, white collar occupations in IT and construction, and investigate its main determinants. Results indicate that there is substantial heterogeneity in the intention to reskill across various jobseeker groups, but also within-group across different types of training programs. Estimates of the willingness to pay for different training features indicate that participants value positively a higher job-finding rate post-training and positively value reskilling in IT, but would need to be compensated for engaging in reskilling in construction. Age, occupational identity, and beliefs regarding monetary and social status returns in high-demand occupations are primary factors influencing reskilling intentions. We implement two different types of policy experiments to understand how to stimulate interest in reskilling. First, we find that a light-touch randomised informational treatment is effective in increasing both self-reported interest and real-life reskilling engagement. Second, policy simulations show that unconditional training subsidies may not lead to higher take-up of reskilling.

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1 Introduction

In the last decades, labor markets have experienced profound changes driven by technology advancements (Acemoglu and Restrepo, 2018; Karabarbounis and Neiman, 2014), globalization (Autor et al., 2013), demographic shifts, and the imperative of a rapid net-zero transition. These transformative forces have led to sectoral shifts, altered consumption patterns, and led to dramatic changes in the type of skills and occupations needed in the workforce. As a result, workers are faced with the challenge of swiftly updating their skillsets to remain competitive and avoid being left behind in the modernizing labor landscape (OECD, 2023a).

Although there is widespread recognition of the importance of skills acquisition to help workers navigate these transitions, participation in training programs continues to be surprisingly low.[1] Across European countries, only 12% of adults received formal or non-formal education and training in the last month (Eurostat, 2022b). Participation rates among low-skilled adults are substantially lower than among their high-skilled counterparts (OECD, 2019a), raising concerns about potential "low-skill traps" among vulnerable workers (OECD, 2018; Burdett and Smith, 2002).

Weak jobseekers' demand for training is commonly mentioned as a reason for limited take-up of adult training programs by policymakers and firms alike. In several countries, the implementation of active labor market policies is complicated by inadequate engagement by targeted beneficiaries (Crépon and Van Den Berg, 2016). Similarly, encouraging employees' participation in upskilling and reskilling programs in firms is costly (Tamayo et al., 2023). In addition, studies have shown that selection into training is negatively related to training needs (Sandvik et al., 2021), implying that demand-side frictions may exacerbate inequalities between high-skilled and low-skilled workers. Yet, we have limited evidence on what the main demand-side barriers to training participation are, and how different policies may help overcome them.

Our paper aims to fill this gap in the literature by studying the demand for training in a large sample of job seekers in Italy, where training needs are particularly pronounced. Compared to other OECD countries, the adult population in Italy exhibits lower levels of numeracy and literacy rates, a significant proportion of NEET (Not in Education, Employment, or Training) individuals, a high share of workers perceiving to be over and under qualified for their job, and a high share of firms

[1] Bauer et al. (2016); Goller et al. (2021); Lechner and Wunsch (2009); Leung and Pei (2023); Rinne and Uhlendorff (2013) provide evidence of the benefits of training programs for the unemployed across several countries. In a meta analysis paper (Card et al., 2018) find that training programs for the unemployed improve employment prospects, especially in the long run, for the long term unemployed and for low skilled individuals. They report better results for programs that combine classroom training with practical experience (apprenticeships or internships).

reporting difficulties in recruiting workers with the right skills. Italy also has much lower participation rates in work-related training activities compared to other OECD countries (Fialho et al., 2019). Recent policy interventions have tried to stimulate participation in training through administrative reforms, including the provision of subsidies tied to participation in training activities. To date, however, the success of these interventions remains limited.[2]

Understanding the drivers of the demand for training (including its sensitivity to monetary incentives) is complicated by two major factors. First, demand and supply of training are jointly determined. For example, the quality of available training courses may affect participants' expectations of returns from training, which in turn affects their demand.[3] Indeed, Italy suffers from a perceived lack of high quality training programs, and often minimal or nonexistent quality assurance of existing offerings, which are based on old catalogs that are poorly aligned with local labor demand (OECD, 2023b).[4] Second, the demand for training may also be highly heterogeneous depending on participants' characteristics and training features, and thus hard to capture in the aggregate.[5]

To overcome these empirical challenges, we study the demand for training in a controlled survey environment conducted in cooperation with one of the largest networks of public employment services in Italy. Our design addresses the supply-side concerns discussed above by focusing on training programs specialized in preparing potential jobseekers for specific occupations that are rapidly growing and typically result in concrete job outcomes for participants upon completion. In practice, this means that at the beginning of the survey each respondent is randomly assigned to occupations (labeled as "treatment occupation" from hereon), and is shown only questions and training scenarios referred to the treatment occupation. For tractability, we focus on reskilling opportunities for two occupations: ICT support specialist and construction technician. Both occupations are in current and expected high demand in Italy (based on vacancy rates),[6] offer high-paying entry jobs, have no

[2]To promote participation into training programs for the unemployed, Italy's National Recovery and Resilience Plan envisaged the "GOL" program, Garanzia Occupazione Lavoro. It has resources of 4.4 billion euros and by the end of the program is supposed to involve 3 million beneficiaries, of which 800,000 in training activities. According to the last report, at the end of 2024, however, only 10% of the 2 million beneficiaries enrolled so far were engaged in training activities (ANPAL, 2024).

[3]An important feature is, for example, whether the program offers a direct connections with concrete job opportunities after training.

[4]On a more positive note, a study conducted by the Piedmont region to evaluate the employment effects of vocational training in the region concluded that, twelve months after completion, the employment rate of participants was 6.6 percentage points higher compared to the control group (Piemonte, 2022). The positive employment effects were more pronounced among men, foreign participants, and older individuals. However, no significant effects were found for those seeking their first job.

[5]For example, Katz et al. (2022) show that successful sectoral employment programs include extensive screening of possible participants on behavioral traits, as well as the provision of wrap-around services.

[6]The WEF (World Economic Forum, 2025) mentions such occupations among the ones with large and positive net predicted growth worldwide over the period 2025-30. In their report, they advocate for reskilling in such jobs.

need for college degrees, and may be accessed through relatively short reskilling programs leading to concrete job opportunities.[7] Additionally, since the two occupations vary in their perceived social status—specifically, construction technicians are embedded in a sector that is perceived to be low-skill and male-dominated (Carranza, 2023)—this set up also allows us to quantify the importance of non-wage related sectoral characteristics in driving the demand for reskilling among jobseekers.

We explicitly consider the possibility that the motivation to train may be highly heterogeneous across individuals by modeling training choices as being jointly determined by preferences, constraints and beliefs on the returns to investment of education, which may vary along both objective and subjective differences across participants.To empirically estimate the relevance of these factors, we collect a rich set of individual characteristics that are typically measured in jobcenters (demographics, work experience, past participation in training, and skills), as well as other variables that are typically not measured, such as beliefs about the returns to reskilling, labor market expectations, and perceived fit and attitudes towards the two proposed high-demand occupations. These data allow us to explore the role of different determinants of training engagement, including psychological factors and perceptions related to the prospective occupations that are heterogeneous across respondents, but not usually measured by job counselors.

Next, to provide a more detailed sense of how the interest in training varies across individuals as a function of their characteristics and/or programs' features, we employ a discrete choice experiment design—whereby respondents make a series of binary choices between generic training and reskilling in one of the exogenously assigned treatment occupations. Each scenario includes a set of exogenously-varied characteristics such as the price, delivery, structure and job finding rate of the programs. This stated-preference methodology allows us to recover a continuous monetary estimate workers' willingness to pay for each training feature, starting with whether the training is generic or specific to the treatment occupations (that is, if the program involves reskilling), conditional on individual characteristics. Additionally, the approach allows us to recover whether the willingness to pay varies across participants along both observable and unobservable characteristics. While the stated choices are hypothetical, we provide evidence that they correlate with an incentivized question about reskilling preferences as well as respondents' real-life engagement in training.

We show four main sets of results. First, we find that the demand for reskilling is highly hetero-

[7] Typically these training courses last between 60 and 100 hours. Courses in IT are offered by the regions and involve beneficiaries of all ages, courses in construction are offered by the building contractors trade association and target mostly young workers (ANPAL, 2022, 2024).

geneous across occupations, despite their identical job finding rate, wage and career prospects in the survey. Respondents are on average willing to pay 3.7 Euros per hour for a reskilling program in IT, but would need to be compensated with 7.3 Euros per hour for reskilling in construction. While women are on average much less interested in the construction occupation, this difference is also driven by subjective factors that are not gender-specific: specifically, willingness to pay for training is especially low among respondents who are less likely to report that a job in construction is a good fit with their identity, that they have the right skills for the job, or that they are interested in it. The difference in interest between IT and construction arises even if the share of (self-reported) overlapping skills with the two occupations are very similar. These findings provide some initial indication that the demand for training is highly dependent on perceived job characteristics and personal factors that go well beyond skill adjacency, prospected wages and future career opportunities, a point that is often missing in public discussions on reskilling.[8]

Second, when we consider the demand for reskilling *within* occupations, we find both socio-demographic characteristics and individual beliefs to matter for training choices. For example, reskilling intentions are particularly low for older respondents, for jobseekers who hold pessimistic beliefs on the potential labor market returns of moving into IT or construction, and those who question how their identity would fit within these industries. This evidence underscores the importance of psychological factors in driving interest in reskilling. We also find evidence suggesting an important role for informational frictions (and, specifically, the disconnect between respondents' perceptions and actual wage and career benefits offered by the treatment occupations) in shaping training choices.

Third, while the demand for reskilling varies along the aforementioned dimensions (i.e., treatment occupation, age, beliefs), there is also substantial unexplained heterogeneity in training choices within specific socio-demographic categories. For instance, even if men are on average more willing to reskill than women, the distribution of willingness-to-pay for reskilling for the same occupation by gender overlaps for most of the relevant ranges. We find similar patterns when splitting the sample by age, or education. Even when considering additional factors, such as perceptions of in-demand occupations or perceived psychological costs, our analysis reveals that we can explain at most one-fifth of the variation in reskilling choices with our survey variables. This underscores the importance for counselors and coaches to dedicate time to gain a deeper understanding of their ben-

[8] For instance, World Economic Forum (2025) primarily mentions funding as a barrier to reskilling.

eficiaries' beliefs, attitudes, and psychological barriers towards reskilling, well beyond measurable socio-demographic characteristics and beliefs.

Fourth, providing information about the labor market returns to reskilling can be an effective way to increase participation in training. To make this point, we randomize a third of the sample to receive information about the wage and vacancies in the occupations targeted by our reskilling programs. This is a light-touch treatment akin to the type of advice that caseworkers may easily provide to jobseekers as part of their counseling services. One-minute informational video increases demand for reskilling by 11%, which is equivalent to cutting the median gender gap in reskilling willingness by half.[9] Our randomized information not only boosts reskilling intentions, but also leads to higher real-life participation after the survey—though this effect is only seen in the group assigned to the IT occupation.

We conclude by asking what is the role of policymaking in shaping the demand for reskilling. Can stronger incentives set up by governments (e.g., subsidies) encourage participation into reskilling? In particular, can they motivate into reskilling the 25% of the sample which does not react at all to information provision? By exploiting our discrete choice model estimates, we compare the effects of generic training subsidies to interventions supporting reskilling initiatives on uptake rates across different courses. Our simulations suggest that, given the multi-dimensional factors driving the demand for training, untargeted training subsidies are not enough to boost reskilling take-up rates. A combination of conditional subsidies, program curation, and communication is necessary to shift market shares towards reskilling for both occupations.

Our paper contributes to three streams of literature. First, this study relates to papers focusing 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; Bassanini, 2004). Studies have shown that certain kinds of sectoral training programs can be effective in improving labor market opportunities for participants, especially when combined with appropriate selection and wrap-around services, such as job referrals (Katz et al., 2022; Schochet, 2001). In the Italian context, Bazzoli et al. (2023) show positive effects of long (400 hours) reskilling programs coupled with work experience.[10] 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). A related stream of work

[9] We show that the effect is mainly seen in respondents who initially underestimated wages in the given occupation. This suggests that their beliefs genuinely changed based on the information provided.

[10] In Italy, some papers also show a positive effect of active labor market policies and incentives for jobseekers' reemployment (Zanella and Salomone, 2025; Kluve, 2010).

focuses on the firm investment choice in training, exploring the conditions under which firms invest in general or specific training (Becker, 1962; Autor, 2001; Acemoglu and Pischke, 1998) and the potential returns (Lyons, 2020; Martins, 2021; Adhvaryu et al., 2023). To the best of our knowledge, work on understanding the demand for training and reskilling is scant. Exceptions are the paper by Bassanini and Ok (2004), who try to disentangle demand and supply of training in explaining take-up across OECD countries, and 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.

Second, we contribute to the literature on the impact of information on educational and occupational choices. Several studies use randomized control trials (RCTs) to test the effects of information provision about higher education on educational enrollment and attainment (Hoxby et al.; Goux et al., 2014; Kerr et al., 2020; Bächli et al., 2025). Among jobseekers, Altmann et al. (2018) test the impact of providing information on the consequences of unemployment and advice on job search strategies on employment duration in Germany. Belot et al. (2019) develop a tool linking jobseekers' former employment with related occupations and up-to-date information on the demand for those jobs. Testing this instrument in an RCT, they find that treated people increased the breadth of job search by 0.2 standard deviations. Behaghel et al. (2022) explore the employment effects of directing jobseekers' applications towards firms likely to recruit on an Internet platform developed by the French public employment service. We add to this work by showing the impact of providing information on labor market conditions on reskilling choices, which may be a necessary first step to moving into higher-quality jobs.

Third, we bring new methods into the study of training choices. Discrete choice experiments have been used in a wide range of contexts, from urban transport choices to workplace amenities (Maestas et al., 2023; Wiswall and Zafar, 2018) and education (Di Stasio, 2014). To the best of our knowledge, there has been no application in the setting of adult training programs, and labor market policies in general.

In the policy realm, this research strives to contribute to the effective allocation of investments in training programs and the formulation of policies that promote a dynamic and adaptable labor force capable of thriving amidst ongoing labor market transformations. Ultimately, the findings from this study can serve as a valuable resource for policymakers, researchers, and stakeholders seeking to enhance workforce development strategies and foster economic resilience in an ever-evolving global

labor landscape.

The paper is structured as follows. Section 2 describes the institutional context, including the organization of adult training in Italy. Section 3 explains our survey design, covering the selection of treatment occupations, our sample, and additional administrative data. We also validate our hypothetical choices by showing their correlation with real-life or incentivized decisions (subsection 3.5). Section 4 describes respondents' reskilling intentions and explores their main individual-level correlates. Section 5 uses a discrete choice model to quantify a willingness to pay for reskilling, and provides benchmarks against the evaluation of other course features. Section 6 asks whether the demand for reskilling can be reshaped through policy. Section 7 concludes.

2 Institutional Context

Skill shortages are widespread in Italy. According to the latest OECD Survey of Adults Skills (PIAAC), 35% of Italian adults between 16 and 65 years old have low literacy and numeracy proficiency (OECD, 2024). Skills shortages are especially severe in high-demand sectors such as IT and STEM-related industries. The absence of adequate skills translates into significant labor market mismatches. The share of under-qualified workers in Italy is among the highest across OECD countries, especially in the South (Garda, 2017). Moreover, the country has the second highest share of NEET in the European Union after Romania (Eurostat, 2022a).

Recently, Italian policy makers have sought to alleviate these inefficiencies through massive investments in training, especially after COVID.[11] However, participation rates in adult training programs remain very low. According to the PIAAC survey (2021)[12] only less than 5% of low-skilled workers take-up any job-related training program in Italy.[13] Rates are similar in France, Spain, or Germany, but are two or three times higher in countries in northern Europe such as Denmark (at 15% take up) or Sweden (at 20%). Among Italian medium and high-skill workers, participation rates stand at 15%, compared to rates of at least 20% in Northern Europe. Like in most OECD countries, Italian workers cite lack of time, cost, and family commitments as the main barriers to training (OECD, 2021). However, even free courses designed specifically for unemployed job seekers

[11] Training was included as one of the key missions of the National Recovery and Resilience Plan set up after the Covid-19 pandemic, leading to the creation of the "GOL" program, a packet of active labor market policy interventions aimed at the unemployed (ANPAL, 2024).

[12] https://www.oecd.org/skills/piaac/

[13] This number increased to 10% after the intriduction of the GOL program (ANPAL, 2024).

often struggle to attract participants.

Despite these challenges, evidence suggests that well-designed training initiatives—particularly those aligned with labor market needs—can be effective in Italy. Studies have shown that reskilling programs targeting sectors with high demand, such as healthcare and digital technologies, can increase job placement rates, especially when tailored to local labor market conditions. For instance, European Social Fund (ESF) programs in regions like Bolzano have demonstrated positive effects on employment outcomes by linking training to specific labor market needs and providing participants with the skills required by local industries (Pastore and Pompili, 2022). Furthermore, the OECD report on Italy's skills strategy emphasizes that aligning training programs with regional labor market demands and fostering public-private partnerships can significantly improve training effectiveness and labor market integration (OECD, 2017). These findings suggest that expanding and improving access to targeted reskilling programs could play a crucial role in addressing Italy's labor market mismatches, particularly for displaced or low-skilled workers.

Yet, reskilling programs remain limited due to a mix of supply and demand issues. On the supply side, training for the *unemployed* and for the youth in search of first employment—which is the focus of this paper—is coordinated by multiple institutional players at national and regional levels.[14] Vocational training for adults is offered by a wide range of different public and private providers and includes programs leading to upper secondary VET qualifications. Private providers of training programs are certified and paid by the regions with regional or European funds. Public training programs are provided by provincial adult education centers (CPIA) under the remit of the Ministry of Education. Sectoral Training Funds (i.e. *Fondi paritetici interprofessionali per la formazione continua*), jointly run by employers and trade unions, also play a significant role in encouraging firms to provide training for their workers (OECD, 2019c). Because of the variety of players involved and the lack of central quality assurance, training opportunities are typically not well connected with actual labor market needs,[15] heterogeneous in quality, and unevenly distributed across regions.[16] The large numbers of certified training providers makes it hard for jobseekers to screen training quality autonomously. These inefficiencies are compounded by the fact that employment services

[14]The State establishes general rules and determines the fundamental principles of education; the regions have legislative power over vocational training programs while education falls under the scope of concomitant legislation.

[15]For instance, a granular analysis matching skills requirements in online job postings to the training offered in an Italian region shows that courses for beauticians and hairdressers account for 3.9% and 2.7% of available spots, compared to a labor demand of 0.4% and 0.2% respectively (OECD, 2023c)

[16]The average low quality of training programs is in part explained by the fact that Italy has one of the lowest spending on active labor market policies across OECD countries (OECD, 2019b), and one of the highest jobseeker-to-staff ratios in public employment services (OECD, 2017)

agencies–public and private organizations offering free guidance and counseling services related to job search and training–typically face very stringent budget and time constraints. The uncertain and uneven supply of high-quality training opportunities makes it difficult to infer the relevance of demand-related factors just from take-up rates. We explain our empirical strategy to overcome this identification challenge in the next section.

On the demand side, on top of the usual barriers to training such as lack of time, family constraints, and costs, a number of other frictions may be at play. First, the demand for training may be depressed by information frictions, such as limited information labor market trends, which might lead to overoptimism in the ability to find employment in a preferred occupation without the need to train or reskill (Mueller and Spinnewijn, 2023). Incomplete or asymmetric information about returns to training can result in suboptimal investment in human capital, particularly when workers underestimate skill depreciation or fail to anticipate future technological disruptions (Jensen, 2010). Psychological barriers may further exacerbate these informational gaps: identity-related concerns, such as those explored by Akerlof and Kranton (2000), suggest that individuals may resist training because it challenges their self-concept, leading to cognitive dissonance and a reluctance to pursue skill acquisition that necessitates a shift in professional identity. Additionally, in labor markets dominated by informal job search channels, such as the Italian one, workers may fear that reskilling or changing career paths will sever existing professional networks, thereby reducing access to job opportunities that rely on personal referrals (Calvó-Armengol and Jackson, 2004). The fear of losing past networks may further discourage workers' search for new opportunities. Such dynamics can significantly weaken the perceived necessity of training, even in the presence of clear economic incentives.

Our paper focuses on the demand side and tries to disentangle the factors that may explain the overall very limited participation rates in training.

3 Survey design and data

This section outlines the survey structure, the treatments between and across occupations, the recruitment strategy, and basic summary statistics about the sample.

3.1 Survey structure

The survey instrument consists of four parts (see Figure 1 for a visualization of the survey structure).

Screening We screen participants on the basis of the eligibility criteria (to be eligible, participants have to be between 18 and 55, be unemployed, and not being enrolled in any training course) and we collect some basic demographic characteristics (e.g. highest education level achieved, whether the person has children and gender).

Basic socio-demographic characteristics and assignment to treatment occupations In the second section of the survey, we ask respondents about their past training and work experience, whether they felt their past job was part of their identity, the skills needed in their previous job and expectations of training effectiveness and job finding rates for the main job they are searching for (which we label a "search occupation").

We then randomly assign every survey respondent to a "treatment occupation" which could be IT or civil construction technician,[17] and we ask about their expectations of wages, job finding rates, employer's demand, confidence in skills, identity fit, and interest in this occupation.

Discrete choice module and within survey treatments In the third section of the survey, respondents are asked to choose between training options with randomized features.[18] We also randomize a subset of participants to receive either an informational or a motivational treatment aimed at alleviating frictions that may limit jobseekers' participation in training initiatives.

Final survey questions In the final section of the survey, we collect further demographic information such as whether the person receives unemployment benefits, duration of their unemployment spell, time spent on household chores, and personality traits (risk aversion, trust).[19]

We now describe in more detail the assignment across treatment occupations, the discrete choice experiment, and the within occupation treatements.

[17] The occupations are described in more detail in section 3.1.1.

[18] These are described in subsection 3.1.2

[19] Given that some of the questions in the survey are relatively cognitively demanding, prior to the fieldwork we undertook an in-depth cognitive test of the draft survey with six respondents (three women and three men). During the cognitive test, the respondents were asked to complete the survey in the premises of the survey company and under the supervision of an expert, discussing in detail the phrasing of the questions and the answer items which they were found to be unclear or ambiguous. The feedback received was reflected in the final version of the survey.

3.1.1 Randomization across occupations

After screening, we randomly assign respondents to one of two high-demand occupations: IT assistant or construction technician. The assignment is stratified by gender (see Figure 2 for details on the randomization). We refer to the occupation assigned to each respondent as "treatment occupation."

Both occupations are in high demand in Italy, and in many other European countries. Figure A1 shows that the vacancy rates in the sectors of both occupations were among the highest in Italy in 2023. The demand for ICT support technicians has been spurred by firms' adoption of new technologies, and in 2022 this occupation was the 1^{st} in terms of vacancy rates in online vacancies in Lombardy.[20] Moreover, Figure A2 plots the average job vacancy rate[21] (2021-22 average) by industrial sector in several European countries. In the Euro Area, the Construction and the ICT sectors are respectively the 2^{nd} and 3^{rd} sectors in terms of vacancy rate. Both sectors show high job vacancy rates in all countries but those with weak labor demand. In construction, growth is mainly spurred by government incentives to renovate private buildings, the infrastructure investments foreseen by the Italian recovery plan funded through Next Generation EU[22] and the investments for the green transition more in general Popp et al. (2020); Guiso et al. (2024)). In 2022, jobs for construction technicians were the 4^{th} in terms of vacancy rates in online postings according to data gathered by Wollybi/Lightcast in 2022 in Lombardy.

To make sure that respondents understand the main tasks involved in the treatment occupations, we show them a short video with some basic information about the job, including a definition and some examples of the tasks involved. We also highlight that both occupations are white-collar and are mainly performed in the office, including the construction technician, which is a back-office role and increasingly less likely to require spending time on construction sites (Strandberg and Josephson, 2005).

For a given respondent, all the reskilling courses proposed in the discrete choice module are targeted to the assigned "treatment occupation." In other words, for a person assigned to the treatment occupation of IT assistant, all the reskilling programs in their scenario choices aim to prepare for a job as an IT assistant.

[20] According to data gathered by Wollybi/Lightcast in 2022. Wollybi is a data collection project run by the Lombardy region in Italy (Digital Observatory on the regional labor market, *PoliS-Lombardia*). The data on vacancies come from Lightcast and are made available by the region.

[21] The Job Vacancy rate is defined as the ratio between vacancies and the sum of vacancies and occupied posts. *Source*: Eurostat, 10.2908/jvs_a_rate_r2.

[22] See: https://commission.europa.eu/business-economy-euro/economic-recovery/recovery-and-resilience-facility_en; https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en

3.1.2 Discrete choice experiment

We leverage a discrete choice method experiment to estimate jobseekers' demand for reskilling vis-à-vis generalist training or no training at all, keeping fixed all the other training features. This approach also allows us to estimate participants' willingness to pay for different individual program features (e.g. the willingness to pay for a course that promises a higher job finding rate).

In practice, each respondent is assigned to six binary choices between a generic training program in "Microsoft Office" or a reskilling program in the treatment occupation. Besides their generic vs occupation-specific content, each training program differs in terms of key features: their duration, setting (virtual or in person), price, structure (flexible or full-time), and job finding rate upon completion of the program. We chose these features on the basis of extensive consultations with job counselors and focus groups with jobseekers[23] to be: a) close as possible to real courses available in Italy, but also b) cognitively not too taxing for the participants. Importantly, we also allow respondents to choose an opt-out option. That is, in every choice scenario, we allow the respondent to choose not to do any of the two trainings proposed.[24]

The chosen features are exogenously varied in terms of their levels in order to be balanced across choice scenarios, thus enabling us to estimate the willingness to pay for different types of training. Figure 3 shows an example of binary choice seen by the participants and Figure A4 shows the different factor levels used to construct training options. While we tried to keep the features associated with the generic and reskilling programs to be as similar as possible, it was also important to reflect actual heterogeneity in training opportunities, and specifically that on average generic training courses are on average shorter and are associated with a lower job finding rate. Therefore, by design reskilling options are longer than generic training (200 or 500 hours compared to 80 or 200) and have a higher job finding rate (at least 50% compared to a minimum of 23%). Note that, while the treatment occupation is labeled as IT or construction depending on the exogenous assignment, the different combinations of training features are identical for the two treatment occupations.

We determined which program features to include in the scenarios and their levels through our partnership with jobcenters and focus groups with potential participants. We then built choice scenarios using an efficient design (i.e. a design that, compared to other options, minimizes the

[23] As we discuss in more detail in the next section, we partnered with *"AFOL Metropolitana"*, the consortium of all the public employment agencies in the province of Milan.

[24] We acknowledge that the respondent can choose the opt-out option for many different reasons that may not be related to the proposed alternatives (Campbell and Erdem, 2019).

generalized variance of the parameter estimates). This 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). This method is employed to avoid using a full factorial design, i.e. a design in which each combination of the proposed factors is presented as an alternative to the respondent. The D-efficient design allows precise identification of the parameters of interest while keeping the survey tractable and limiting the cognitive burden for respondents.

We picked 18 binary choice scenarios in total, divided into 3 blocks. Every respondent was randomly assigned to one block only and thus had to make six choices. We also randomized respondents to see one of three variants of every block, which differed only in the order of presentation of the attributes. Empirically, we checked that the design leads to a balanced presentation of levels within and across blocks, as well as no correlation between factors (see Figure A3 for the balance between factors).

3.1.3 Within occupation treatments

We designed two experimental treatments to study the importance of two frictions that may limit jobseekers' participation into training initiatives: lack of information and psychological barriers.[25]

Limited knowledge of the transformations happening in the labor market might contribute to people's overoptimistic expectations of being able to find employment–even within the same occupation–without some degree of reskilling. Qualitative interviews with jobseekers before designing the survey highlighted their struggles in finding easy-to-access and up-to-date information on jobs in demand and skill needs.

In terms of psychological barriers, low self-esteem, fear of rejection and past negative experiences can worsen informational constraints. For instance, these factors may induce resistance to change and anxiety about the prospect of going against one's work-related identity (McKee-Ryan et al., 2005). Such psychological constraints may be especially severe for older jobseekers, or those who only had one occupation in their past.

In practice, we randomize exposure to short videos that provide more detailed information on the wage prospects associated with the treatment occupation (informational treatment) or a motivational

[25] We use the within occupation treatment groups only in Section 6.1, where we estimate the average treatment effect of our experimental treatments. All the other analysis in this paper refer to the control group for which we did not influence behavior with any experimental intervention.

message about learning. We describe the treatments and experimental design in Section 6.1.

3.2 Recruitment

We conducted the survey with two different samples of Italian jobseekers.

3.2.1 Survey-Company Panel

The first sample was recruited through a professional survey company (CE&Co), which runs a panel of 150,000 active members, representative of the entire Italian population.[26] From this panel, we randomly sampled respondents to reach a target of 600 completed interviews by jobseekers aged 18-55, therefore excluding from the sample all employees and the self-employed, as well as persons who are not looking for a job and who are currently undertaking a training. Each prospective respondent was sent the survey via e-mail, and only invited panelists could respond to the survey as the link was individualized and could not be re-used.[27]

Quotas, i.e. constraints on the numbers of respondents with particular characteristics or sets of characteristics, were used to control the characteristics of the final sample to align it with the distribution in terms of age, gender, and geographical area of jobseekers in Italy using the information available in the Labour Force Survey by the Italian statistical institute Istat.

All respondents completing the interview were compensated for taking the survey, as is typical in these kinds of surveys.[28] On average, respondents took 20 minutes to complete the survey. A number of real-time checks were implemented to ensure the quality of responses. First, the link could be used only once to prevent multiple submissions. Second, three recurrent types of misbehavior were identified and blocked: "speeders", i.e. participants who complete a questionnaire in less than 25% of the median length of interview (LOI); "straight-liners", i.e. respondents who in a series of questions, typically items with the same response scale or matrices, always click on the same step of the scale; "happy clickers", i.e. panelists who provide mutually inconsistent responses, answering randomly without reading the question carefully.

A pilot with 25 respondents was undertaken to validate the script of the survey, test the flow, and check whether the questions were clear.

[26] The panelists are recruited via various sources, online and offline (advertisement, emailing, social network, etc.). Membership to the panel is voluntary. At the moment of enrollment, panelists provide their basic socio-demographic information, and a series of quality checks are implemented to ensure that only real individuals are enrolled.

[27] This survey was not accessible to anyone on the web, and panelists could not volunteer to participate.

[28] Incentives consisted of tokens that respondents could redeem from the survey company, for a value of around 5 euros.

3.2.2 Jobseekers registered at job centers in the Metropolitan area of Milan

The second sample was recruited through our partner "AFOL Metropolitana", the consortium of all the public employment agencies in the province of Milan (covering 3 million inhabitants). AFOL supports jobseekers with their administrative paperwork (e.g., to certify unemployment) and provides free-of-charge career guidance, job search assistance, and training. Even if it serves around 30 thousand applicants every year, only a few of them enroll into a training program, either provided by AFOL or other organizations. Once registered at AFOL, one can take up a training course anywhere in the region of Lombardy, and the course is usually paid for by the region if it is within the plan devised to help the applicant. AFOL offers a vast number and a wide range of programs, some of which are provided directly by AFOL personnel (such as personal services, fashion, food and catering, photography, video and design, electric and hydraulic appliances, mechanics for motor vehicles, informatics).

We sent an invitation to participate in our survey to the jobseekers in their registries who registered between January 2022 and July 2023 through the IT system of AFOL Metropolitana. We excluded users with no email address, of foreign nationality, and outside the 18-55 age range. For the users registered in the job centers from September 2022, we also excluded those who had an active employment contract at the moment of the data extraction. Invitations to the survey were sent in three different waves between April and September 2023.[29] We offered an Amazon voucher of 5 euros to the first 500 respondents to the survey. In total, the selected target sample is composed of 44,224 jobseekers. Out of this sample, we received a total of 512 complete answers, for an implied response rate of 1.2%.[30,31]

3.3 Job Postings and Administrative data

We combine our survey data with three sources of administrative data:

[29] Different data extractions were necessary because people register in the job centers on a rolling basis. Moreover, starting in September 2022, the job centers started using a new onboarding procedure for jobseekers. For this reason, we use two distinct survey links for the sample registered before or after September 2022. Assignment to the survey and its treatments is thus effectively stratified by sub-sample.

[30] The implied response rate is a lower bound, since a significant amount of email address were invalid. Similar studies to our report comparable response rate. In Belgium, in an experiment conducted in partnership with a PES, Leduc and Tojerow (2025) report that 5% of their population clicked on the link of their online survey. DellaVigna et al. (2022) report a 9% response rate for their survey, which used both mail and SMS invitations and reminders.

[31] Table A2 shows that, relative to the population of jobseekers registered in the job centers, the CE&Co sample is older, more educated, and has slightly more women than men.

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). Furthermore, we asked *Lightcast* to provide us with measures of skill distances between all occupations and each of our treatment occupations. These distances are computed using their own proprietary algorithm and skill classification based on job postings but broadly correspond to the share of skills in common between two occupations.[32] We cooperated with the *Lightcast* team to perform a match between the occupation (searched and past) provided by our respondent and the ISCO classification exploiting both the title of the occupation and its description.

Administrative data on wages by occupation from *CICO* The CICO[33] 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.

Administrative data on job spell and training experiences for the AFOL sample Finally, we matched the survey responses with administrative data from the AFOL job centers. For each of our respondents from the AFOL sample, we have data on training experiences and employment spells before and after the survey. For each training course a respondent enrolled in, we have information about its content and duration. In terms of employment history, data are extracted from the same source as the *CICO* data and tell us whether our respondents started any job before or after the survey, which occupation they were hired in and in which industrial sector their employer was registered. Differently from the *CICO* data, we do not have information on wages for this sample.

[32] *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 (Cammeraat 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.

[33] *Campione Integrato delle Comunicazioni Obbligatorie*.

3.4 Summary Statistics

Table 1 shows summary statistics by gender for the pooled sample. The average respondent is 40 years old and has 13 years of education. Most of the sample worked in the past but has been unemployed for approximately 40 months. Around 50% of the sample is looking for the same occupation as the main one done in the past, but the majority say that they are looking for more than one occupation and that they would accept a job rather than the main searched one. In terms of past training participation, 55% of participants ever participated in a training course during their adult life. On average, respondents think that they have a 42% probability of finding a job in their searched occupation within the next three months. They believe that being trained would increase this likelihood by at least 11 percentage points, but also that training would only marginally increase their expected wage by around 30 to 60 euros per month.

In terms of gender differences, women in our sample are more likely to be in a stable relationship and to have kids. Accordingly, they are more likely to report not having been employed because of the need to look after their children. Past training experiences, job search behavior, and beliefs about employability look broadly similar between men and women.

Many of our jobseekers share a similar employment history and skillset. The survey asked each respondent to report the main occupation performed in the past through some open-ended text, which includes a keyword and an explanation of the main duties. We assign a unique ESCO code to each of our respondent's answers through a categorization provided for us by the company Lightcast (see subsection 3.3).[34] We find that almost 40% of our respondents concentrate into clerical support or service and sales roles. Reassuringly for our design, only less than 2% of jobseekers has had direct experience in the two treatment occupations.

The Lightcast data contain also a measure of skill distance between a person's past occupation and the treatment occupations, which we can contrast with jobseekers' perceptions elicited in the survey. Figure A12 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,

[34] To perform this match, Lightcast uses a multilingual language model. BERT-PM is a variant of BERT (Bidirectional Encoder Representations from Transformers), a popular language representation model developed by Google. BERT-PM is specifically trained for paraphrase detection across multiple languages. The model is capable of understanding the semantic similarity between pairs of sentences or phrases in various languages. After the classification conducted through the language model, the pairs with the similarity index of lower than 0.6 were manually matched.

indicating that the actual and perceived costs of reskilling may differ (Figure A13). We will examine the possible implications of this misalignment in the next section.

Table 4 shows additional descriptive statistics about respondents' beliefs and perceptions related to the treatment occupation. For both men and women, expectations of being hired and employers' demand are lower in construction than in IT, even though they predict wages to be higher in construction. Respondents are also less likely to report that a job in construction is a good fit with their identity, that they have the right skills for the job, or that they are interested in it.[35] Within each occupation, women are more likely to have worse perceptions of the jobs than men.

Table A6 shows the comparison between the sample and the Italian unemployed and/or inactive population, using data from EU Labour Force Survey (LFS). Individuals in our surveys are slightly older on average than those in the national sample and, accordingly, have more years of education. Partnership and parenthood rates are quite similar across samples, even if our respondents are slightly more likely to have partners compared to the national average. The most important differences are found in terms of the length of the unemployment spell. Job centers' participants have been out of work the longest, indicating potentially higher challenges in re-entering the workforce. The survey company sample shows the shortest duration out of work, possibly reflecting a more transient unemployment status among its respondents. Subsidy receipt shows a similar percentage in the survey and the national average, while it is higher in the AFOL sample. Overall, this table highlights significant differences in the demographic and socioeconomic characteristics of individuals across the three samples, potentially reflecting the varied barriers and opportunities faced by different segments of the workforce.

3.5 External validation of training choices

The training and reskilling choices in our survey are hypothetical. How well do they reflect job seekers' actual behavior and preferences? We use two main approaches to demonstrate that these choices provide meaningful insights into real training decisions.

First, our survey instructions guided choices to be informative of real training behavior. For instance, the survey explicitly asked respondents to think about the decisions they would take in real life when choosing a course, including potential constraints. We also highlighted that there were

[35] The survey included a skills checklist. For each of our treatment occupations, we showed the main skills required according to the classification in O*Net, and respondents had to select the ones they thought they already had.

no right or wrong answers, but we were only interested in what they would choose in their everyday life.

Second, we empirically show that incentivized and real choices are related to the respondents' hypothetical answers in a meaningful way. In the survey instrument sent to jobseekers in the PES, we added an incentivized question that asked respondents to allocate 10 points across real courses offered in the Lombardy region. The list included both generalist training and reskilling options. To incentivize truthful answers, we added the sentence "We may communicate this list to your case worker to help you make training choices among the courses offered in the Region." In the control group, Figure 4a shows that the likelihood of choosing reskilling in the hypothetical scenarios is positively related to the number of tokens assigned to reskilling courses in the incentivized question ($\beta = 0.11$, $p = 0.07$). This suggests that hypothetical scenarios are informative of choices that have real-life consequences for the respondents. A second piece of evidence for the reliability of our measures comes from the AFOL administrative data, where we can see all the training programs undertaken by respondents within the last two years. 20% of the sample engaged in any training in this time period.[36] From the administrative data, we compute the number of training programs attended. Figure 4b correlates the unconditional likelihood of engaging in any training in the administrative data (on the y-axis) with the predicted likelihood of choosing any training in our hypothetical scenarios. We see that the two measures are positively and significantly correlated ($p = 0.10$). Similarly, the number of training courses done in Lombardy (conditional on participating in training) is positively and significantly related with the predicted training from the hypothetical scenarios.

4 Characterizing the demand for reskilling

This section examines reskilling intentions in our sample of Italian job seekers. First, we show that the demand for reskilling is different across occupations: respondents generally prefer reskilling in IT over generic training, while the opposite is true for construction. Next, we analyze individual factors that influence reskilling intentions within occupations, and explore the objective and subjective drivers of training decisions. Finally, we consider the role of informational frictions. Note that these results are based on our control sample, that is the set of respondents that were not involved in the

[36] Administrative data on engagement in training match with self-reports in the survey (where also 20% report having done a training in the past 24 months).

experimental treatments described in Section 3.1.3.

4.1 Differences in reskilling choices across occupations

Figure 5a shows the frequency of choices for different types of courses, pooling both treatment occupations together. 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 opt-out 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 suggests that respondents value reskilling courses as much as generic ones.

This result, however, masks considerable differences across occupations. Figure 5b shows the frequency of choices for different types of courses by treatment 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. Yet, when it comes to choosing between reskilling and generic courses, reskilling in IT is preferred than in construction (p=0.00). Since the wage and career opportunities and the features of the training programs are identical for the two treatment occupations, this difference suggests that other factors—such as, for example, the fact that the construction job is perceived to be of lower social status and less fitting with one's identity relative to the IT occupation, as shown in Table 4—shape the demand for reskilling.

4.2 Differences in reskilling choices within occupations

4.2.1 Job finding rates and program duration

We now turn to consider the importance of different program features in accounting for reskilling choices *within* occupations. First, the willingness to reskill is particularly high in choice scenarios where the reskilling option has a higher job finding rate than the generic training course. In such scenarios, respondents choose a reskilling program 43% of the time in the construction occupation and 53% in the IT one. However, almost 35% of jobseekers never choose the reskilling option even if it displays a higher job finding rate than the alternative in the construction occupation, and 23% in the IT occupation. Furthermore, the marginal impact of higher job finding rates in driving training choices rapidly declines. When the difference in job finding rates between reskilling and general

training is the smallest, jobseekers choose to reskill 42% of the time in the construction occupation (52% in IT); when the difference is largest, they choose to reskill 41% of the time in the construction occupation (49% in IT).

Recall that, on average, reskilling programs are longer than generic training programs. However, we find that a sizeable portion of the respondents does not choose reskilling even when it has both higher job finding rates and a shorter duration than generic training: only 31% of the respondents consistently choose the reskilling option in these cases in the construction treatment arm (39% in the IT occupation). Overall, this evidence suggests that participants' choice to reskill depends on a broader set of considerations beyond program duration and job finding rates such as, for example, participants' socio-demographic characteristics and/or preferences and beliefs. We examine these factors below.

4.2.2 Respondents' characteristics, preferences and beliefs

We use our rich set of survey variables to examine the importance of respondents' characteristics, preferences, and beliefs on training choices. In Figures 6a and 6b we present the analysis and show the coefficients of multivariate linear models at the individual level, in which the dependent variable is the share of times (out of 6) a respondent chose the reskilling option as their preferred one. The independent regressors are different individual factors, as described in more detail below. Each regression includes controls for the dataset used (CE&Co or AFOL), and basic respondent's characteristics that may differ between the two data collection samples (i.e., length of unemployment, subsidy reception, and region of residence). Therefore, the coefficients report the impact of different individual characteristics on reskilling intentions for people exposed to the same treatment occupations, residing in the same geographical area, and with similar unemployment length and subsidies. Figure 6a pools together choices across the two occupational treatment groups, while Figure 6b shows results by treatment occupation.

Demographic characteristics The first three coefficients in Figure 6a explore the role of gender, age, and education on the share of reskilling choices. In general, being a woman, being older than 40, or being highly educated are all negatively related to the propensity to reskill. In univariate regressions, each of these variables has a negative, statistically significant, and sizable relationship with reskilling (respectively, $\beta = -0.075$ and p=0.01 for the above-median age dummy; $\beta = -0.068$ and p=0.03 for

the female dummy; $\beta = 0.014$ and p=0.72 for the high education dummy). In multivariate analysis, only the dummy for being older than 40 (i.e. being above the median age in the sample) retains a statistically significant effect. This is the case for both reskilling in IT and Construction, with similar magnitudes.

Time Constraints The second set of coefficients in Figures 6a and 6b investigates whether jobseekers' time constraints explain their likelihood of choosing reskilling rather than generic training or the opt-out option. We proxy for time constraints using an index of job search intensity (hours spent looking for a job daily per occupation searched) and an index of household commitments (average hours spent on household chores and the number of children). These variables are not significantly related to reskilling choices. This null result may point to a limited role of constraints in explaining the choice of reskilling, or that respondents do not fully internalize real-life constraints when selecting their preferred option in our hypothetical scenarios.

Past training exposure We find in Figures 6a and 6b that having participated in training in the past has a negative relationship with reskilling. This effect is not driven by jobseekers' negative experiences with training, as we find that opinions about past courses are positive in our sample: the average respondent gives a rating of 7 out of 10 in terms of satisfaction with their course. A plausible explanation is that participation into a course crowds out future further engagement, as jobseekers may have declining marginal returns from participating in multiple initiatives or set aside only a limited amount of time to dedicate to training.

Skills distance from treatment occupations We also look at the relationship between reskilling intentions and the self-reported share of skills overlapping with the treatment occupations. These are important to consider since the costs and returns associated with reskilling can vary significantly based on an individual's personal circumstances. For example, transitioning to IT assistant may be less challenging from web development than from being a taxi driver. We thus expect individuals whose past occupations are very different from IT or construction to have higher reskilling costs, and thus to be less likely to choose reskilling in our scenarios. As expected, we find in Figures 6a and 6b that the share of self-reported skills for the treatment occupation is weakly associated with higher reskilling intentions in both IT and construction.

Expected returns of treatment occupations Next, we examine the role of expected wage and occupational benefits for reskilling intentions. We start by examining the role of beliefs about employers' demand or expected wages in someone's search (i.e., favorite) occupation. This is because individuals who are already searching for an in-demand occupation may be less inclined to engage in reskilling. In general, however, these beliefs are not significantly correlated with the intention to reskill. Jobseekers who search for more rewarding and ambitious jobs are equally likely to choose reskilling in our scenarios as their less ambitious peers.[37]

We then turn to the beliefs about the treatment occupations. More optimistic beliefs about the labor market returns to the treatment occupation are positively and statistically significantly related to reskilling intentions, though these results are generally much stronger for the IT than the construction occupation. Jobseekers who expect a high demand[38] by employers in the treatment occupations have a 6 percentage points higher share of reskilling shares in their choices. The belief that the reskilling program will lead to higher wages matters for the choices, but interestingly this result is entirely driven by the IT occupation. The demand for training for the construction occupation seems less sensitive to expected wages.

Occupational identity Turning to psychological factors, we consider the importance of perceived occupational identity, either related to the past or the treatment occupation. Both skills and identity are strongly predictive of training choices. On average, a person's confidence in their ability to perform well in the treatment occupation positively predicts reskilling intentions, pointing to a key role of psychological factors related to self-confidence and perceived competence in encouraging reskilling. Indeed, a striking result emerging from Figure 6a is that a person's identity fit with the treatment occupation is one of the most important correlates of reskilling choices, both in terms of coefficient magnitude and precision. A standard deviation increase in an index of identification with the treatment occupation is associated with 8 percentage points increase in reskilling frequency, which represents 17% of the mean rate of reskilling. This suggests that preferences for reskilling are strongly affected by psychological factors, such as a sense of belonging in the treatment occupation. These findings highlight the significant role of identity and self-perception in shaping career-related decisions, emphasizing the importance of considering psychological motivators alongside economic

[37] More optimistic expectations on the job finding rate of the search occupation are positively correlated with reskilling in the pooled sample. Results are weaker, though generally less so for IT, in the split samples.

[38] We collect in a categorical variable expectations about labor demand in treatment and searched occupations. Values for expected demand are "Very low", "low", "high", "very high", "I don't know". Jobseekers who expect a high demand are those who answer "high" or "very high".

incentives in designing effective reskilling interventions. The influence of occupational identity on reskilling is similar for both IT and construction.

Another important psychological factor emerging from the data is that jobseekers who perceive the treatment occupation to be associated with low social status are less likely to opt for reskilling in their choices, though this result is entirely driven by the IT sector.[39] Overall, this evidence suggests that the expected returns from reskilling–either in terms of labor market outcomes or social prestige–matter for training choices.

Comparison with generic training An interesting question to explore is whether the factors associated with reskilling choices also matter for generic training. To examine this point, Table A4 compares the explanatory power of our survey variables on respondents' choices of generic training versus reskilling through a multinomial logit model. The model provides the marginal increase in the likelihood of picking a certain course (generic vs reskilling) compared to the opt-out option when the given regressor increases by one unit. We find that most of the measures that are predictive of reskilling according to Figure 6a do not equally predict the choice of generic training (e.g., being above 40, occupational identity in the treatment occupation). While the signs are similar in many instances (e.g., being above 40 is associated with lower reskilling as well as lower training), the marginal effects on generic training tend to be smaller and non statistically significant. The key correlates of reskilling commented so far can thus be interpreted as specific to specialized training in in-demand occupations rather than to generic training.[40]

4.2.3 Information frictions

A rich literature has shown the important role of incorrect beliefs on investment in education (Jensen, 2010; Reuben et al., 2017; Boneva et al., 2022) and job search (Jäger et al., 2024). These frictions may also apply in our setting: jobseekers may hold inaccurate beliefs that can alter their willingness to undertake training. For instance, limited awareness of one's own skills may lead potential trainees to overestimate reskilling costs. Similarly, over-optimism about job prospects in their preferred search occupation can decrease the perceived returns from reskilling (Mueller et al., 2021).

[39] Recall that the % of respondents reporting construction to be associated with lower social status is significantly higher in construction relative to IT, so it may be harder to identify the relative importance of this variable within occupations and gender.

[40] Table A5 shows tests for the equality of coefficients between generic training and reskilling estimated in our multinomial logit model used for Table A4.

We analyze the relevance of information frictions for training decisions by comparing respondents' perceived benefits and costs of reskilling, as measured in our survey, with average actual benefits and costs, as measured by combining administrative data with information about jobseekers' searched and/or past occupation and regional location. We interpret a greater distance between perceived vs. actual costs/benefits as evidence of information frictions, and we study the extent to which the presence of information frictions predict training choices.

Perceived vs. actual returns of reskilling We measure the returns to reskilling as the log ratio between the expected wages in the treatment occupation relative to that in the "search" occupation, that is the occupation where jobseekers are focusing their search efforts. "Actual expected returns" are measured by taking the average wage of the two occupations in Italy (derived from administrative CICO data), weighted by the share of job openings for that occupation in the jobseeker's region (from Lightcast data). This gives us a rough measure of the benefits of reskilling into the treatment occupations for jobseekers who live in the same region, have had the same main past occupation and/or search for the same preferred occupation.[41] For "perceived expected returns", we use a similar approach and build the ratio between the expected wage for the search occupation reported by the respondent, weighted it by the jobseeker's belief on the likelihood of being hired in that occupation in the following 3 months, and the same object for the treatment occupation.[42]

Figure A8 shows the distributions of our perceived and actual returns measures in the sample. For 50% of our sample, the estimates of actual returns from reskilling are substantial: jobseekers expect to gain 440 monthly euros more if switching from their targeted job to the reskilling occupation. This increase represents 31% of the median monthly wage across all occupations in Italy. There is also substantial variation in expectations, with the 25th percentile believing that they would lose 200 euros and the 75th that would gain 200 euros from switching into the treatment occupation.

Figures A9a and shows the sample divided into four quadrants, according to whether perceived and actual returns match. We allocate respondents into a high vs. low level of actual and perceived benefits by taking the log difference between a person's level of returns from the sample average. Using this criterion, perceptions and actual estimates match for 44% of the sample. Mismatches

[41] 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.

[42] We use this weighting to discount wages by the chance of getting a job. For the actual version of the weighted wages, we use the vacancy ratio. For the perceived version, we use the respondent beliefs on the possibility of finding the treatment or searched job (e.g.: the respondents states that she has a 60% of finding a job as an IT assistant, hence we weight the expected wage by this percentage).

arise for two reasons: 23% of our sample perceive to have high returns from reskilling, while their estimated average actual returns are negative, and 33% of the sample believes to have negative returns from reskilling, but their average actual returns are positive.

In Figure A9b we show that both perceived and actual returns matter for reskilling choices. Respondents classified as having high returns–both according to their own perceptions or our admin data–choose reskilling in 43% of their scenarios. In contrast, respondents with low actual and perceived returns choose reskilling in 38% of their choices.

Perceived vs. actual costs of reskilling We measure the "actual costs" of reskilling as the skills distance between a jobseeker's main past occupation and the treatment occupation, as computed using the Lightcast methodology. "Perceived costs" are similarly defined as the perceived distance in skills between a jobseeker's main past occupation and the treatment occupation, as reported by participants in the survey in the skills checklist. To define a high vs. low level of costs, we take the difference between a person's level of costs and the in sample average distance. Figure A10 shows the average actual and perceived shares of overlapping skills. On average, only half of the sample has at least 30% of the skills required in the treatment occupations.

We combine actual vs. perceived costs in Figures A11a and A11b. For around 28% of our sample, the perceived skill distance from the treatment occupations is substantial, both in terms of perceived and actual skills distance: they report to have less than 50% skills needed to perform the treatment occupation, and this is confirmed by the Lightcast analysis. Perceptions and average costs match for around 60% of jobseekers who correctly perceive to have either lower or higher costs than average. These respondents belong to the diagonal quadrant of the matrix in Figure A11a. However, 40% of respondents either under- or over-estimate their reskilling costs (cross-diagonal quadrants of Figure A11a). Over-estimation is particularly large, with a third of the sample reporting a skill-distance with the treatment occupation that is above average, even if their expertise inferred by Lightcast is more aligned to the treatment occupation.

Figure A11b, however, suggests that possible misperceptions of reskilling costs do not predict reskilling choices, as the frequency of reskilling is very similar across all quadrants of Figure A11a. This evidence points to a limited role of skill fit as a determinant for reskilling choices. This can be because jobseekers are not aware of the skills needed in the treatment occupation, or because the relative costs related to learning new skills are overlooked compared to other types of costs (e.g.,

out-of-pocket or time costs).

4.3 Summary

The analysis so far shows that reskilling intentions depend on a range of factors that go beyond average wage and career opportunities associated with the treatment jobs.

First, even if we purposely chose two similar white-collar entry-level jobs, our findings suggest the industrial sector in which the occupation is embedded is a key factor for training choice. In particular, construction seems to be a particularly hard sector to reskill people due to the perceived lack of prestige of the occupation, and misalignment of professional identity.

Second, individual characteristics, occupational preferences, and beliefs are key correlates of reskilling intentions. We find that age, occupational identity, and perceived returns are the primary drivers of differences in reskilling intentions.

Third, we show that reskilling choices are also partly explained by the presence of information frictions. In particular, respondents with more accurate perceptions of the actual benefits of switching to the treatment occupation relative to their search occupation are more likely to opt to reskill.

Note also that detailed information on job experience and personal attitudes, which are rarely part of caseworkers' information set anyways, jointly explain only less than one-fifth of the variance in the data, implying that there is unobserved heterogeneity in reskilling choices even within observably similar individuals. Even including the full set of survey variables explains only up to 16% of the variation in reskilling choices across participants (Figure A5), highlighting the difficulty of predicting jobseekers' willingness to reskill based on observables. This suggests that training choices are highly heterogeneous across individuals, even when they share similar observable characteristics.

Additionally, we see that course features significantly influence respondents' choices (Figure 7). In our sample, over 80% of respondents adjust their preferred option based on the characteristics of the available courses. In contrast, fewer than 10% consistently choose the same type of training across all scenarios. This suggests that respondents carefully evaluate course attributes, highlighting the importance of program features in shaping reskilling decisions.

Taken together, these findings suggest that it is important to empirically evaluate the relevance of both factors—heterogeneous preferences and course features—as possible determinants of the demand for training. We consider these factors in the next section by estimating a discrete choice model. This methodology provides us with a more nuanced and continuous assessment of the

willingness to pay to reskill.

5 Estimating the willingness to pay (WTP) to reskill

In this section we present the results emerging from the discrete choice experiment, in which participants were asked to choose between generic training, reskilling and no training on the basis of a exogenously varied sets of program features: whether the program consists of reskilling for a treatment occupation, program duration, setting (virtual or in person), price, structure (flexible or full-time), and job finding rate upon completion of the program. The repeated choices for the same individual allow us to estimate the relevance of these features—and in particular of reskilling—controlling for individual participants' characteristics and beliefs. Additionally, since choices are translated into a continuous willingness to pay measure, this approach allows us to explore with greater precision the possible heterogeneity of preferences across participants.

5.1 Empirical model

We use a logit model to quantify the marginal impact of course features on training choices *ceteris paribus*. This approach is rooted in Random Utility Models, i.e. participants are assumed to choose the option that maximizes their utility (all coefficients are estimated relative to generic treatment).

We model the utility function as being composed of two additive terms: the indirect utility V_{ij}, which is a linear function of observable individual characteristics (*i*); the scenario of alternative course features (denoted by *j*), and an idiosyncratic unobservable component ε_{ij}. We assume ε_{ij} to follow a Gumbel distribution to be able to estimate the discrete choice model with an alternative-specific conditional logit.

The choice is modeled as:

$$y_{ij} = \alpha_j + \beta_1 \text{content}_j + \beta_2 \text{cost}_j + \beta_3 \text{jfr}_j + \beta_4 \text{duration}_j + \beta_5 \text{delivery}_j + \beta_6 \text{timing}_j + X_i + \varepsilon_{ij} \quad (1)$$

where α_j is an alternative-specific constant, training features vary at the alternative *j* level, and X_i is a vector of individual characteristics examined in the previous section, included as control variables as in Train (2009).[43]

[43] X_i includes controls for: treatment occupation, age, gender, block, length of unemployment, education, past occupation, having any kid, receiving any subsidy expectations, overall skills, having done any training in the past, opinions on training

The family of logit models estimates coefficients up to a scale.[44] To gauge the size of our estimated coefficients, we follow the literature and present the ratio between parameters and the cost coefficient, i.e the Willingness to Pay (WTP) coefficients. The WTP for each factor is indeed defined as the increase in costs that keeps an individual's utility constant given an increase in a specific feature. For instance, for the Job Finding Rate, we can take the total derivative of utility, and keeping its variation constant we obtain:

$$dU = \beta_2 d(cost) + \beta_3 d(jfr) = 0 \implies WTP(\text{jfr}) = \frac{\partial \text{jfr}}{\partial cost} = -\frac{\beta_3}{\beta_2}$$

As in the previous section, we estimate this model on the "control" sample, that is the sample that was not exposed to the information and motivational interventions described in Section 3.1.2.

5.2 Average WTP to reskill and other course features

Table 2 presents the results of the estimation pooling both IT and construction treatments. The marginal utility of moving from a generic training to reskilling is small and not significant (0.025, $p > 0.10$), implying to a WTP for reskilling close to 0 (Column 1 of Table 3). However, in line with the earlier discussion, Columns (2) and (3) of Table 3 show that the average WTP masks large differences across occupations: respondents would be willing to pay 3.7 €per hour to reskill in IT, and they would need to be compensated by 7.3 €per hour to reskill for the construction occupation.

Table 2 also shows the respondents' preferences for different training features. We find that respondents show a strong taste for programs with higher job finding rates. An increase of 10% in the job finding rate is associated with a WTP of approximately 160 euros for a course of 100 hours, which corresponds to slightly more (101%) than the average cost of similar courses in our scenarios. Respondents, however, are almost twice as sensitive to the job finding rate in construction than IT. Respondents also show a distaste for longer training courses, but the magnitude of this effect is quite small: on average a person would demand a 1.8 euros compensation for 120 additional hours of training, with results similar in IT and construction. Job-seekers also prefer in person training courses with respect to online, especially for the IT occupation: there, job-seekers are willing to spend 2.85 €per hour of training. The same coefficient is not statistically significant in the construction

utility, skill share in treatment job, overall expectations on treatment job, identification in treatment job, job search breadth, searching the same job as the last one, survey arm, and geographical region of residence.

[44] Formally, through the logit model we estimate β/σ, where σ is the scale parameter, i.e. the variance of the error term distribution. By taking the ratio of coefficients, we can drop the scale parameter and fully identify the relative coefficients.

occupation. We find no specific preferences for full-time or flexible programs, or for having the option of not choosing any course.

5.3 Heterogeneity in WTP by individual characteristics and beliefs

Figure 8 shows how the willingness to pay for reskilling varies across key respondent characteristics and beliefs.

We see a generally positive willingness to pay for reskilling in IT, regardless of respondents' gender, education, and age, though the WTP is much higher in magnitude for men relative to women (3.5 Euros/hour for women vs 5.9 Euros/hour for men), and for younger workers (5.03 for respondents above 40 years old vs. 4.39 Euros for respondents below 40 years old). The results differ considerably for construction, where women display a striking negative and large WTP for reskilling in construction. Our average female respondent would need to be compensated 7.2 Euros per hour to engage in a training in construction. A similar difference emerges between college and non college educated respondents, and between participants below and above 40 years old. Respondents without a college degree would be willing to pay 1.83 Euros per hour for a reskilling program, while those with a college degree would need to be compensated 5.35 Euros per hour. The average respondent aged 40 or more would need to be paid 5.46 euros per hour to engage in a reskilling program in construction; the average younger counterpart would need to be compensated 1.51 Euros. These differences suggest that training preferences are much more heterogeneous across specific demographics for construction than IT.

There are similar disparities across occupations when we consider the role of beliefs, as shown in Figure 8b. We start by showing the WTP for reskilling separately for respondents with an above- or below-median identity fit with the treatment occupation. For both construction and IT, job-seekers who think that their identity is not aligned with the treatment require some compensation for participating in reskilling, but the required subsidy is much larger in construction (10.5 euros per hour) vs. IT (2.2 euros per hour), indicating that occupational identity is a particularly severe friction when switching into the construction sector. In contrast, the WTP for reskilling is positive for respondents with an above-median perceived identity fit with the treatment occupation across the two occupations. Beliefs on vacancies in the treatment occupation[45] matter for IT (respondents who believe that the treatment occupation is in high demand have a WTP for the reskilling program of

[45] We classify respondents who think that labor demand is "High" or "Very High" as "High vacancy beliefs", while the rest is classified as "Low vacancy beliefs".

6.59 euros per hour), whereas we find a negative WTP for reskilling programs in construction across both high and low vacancy beliefs, suggesting that the potential monetary and occupational benefits do not completely offset the distaste for the construction occupation. We find no heterogeneity in WTP across beliefs on wage (the WTP is generally positive for IT and negative for construction). The last bars of Figure 8b show that beliefs about the social prestige associated with an occupation also significantly affect respondents' willingness to pay for reskilling, particularly in construction.

5.4 Heterogeneity in WTP within demographic categories

We know from the results presented in subsection 4.3 that there is a large unexplained heterogeneity in reskilling, even controlling for individual characteristics and beliefs. The alternative-specific conditional logit that we have used so far does not allow for such heterogeneity, since it implicitly assumes that all respondents with similar observables share the same preferences (*taste homogeneity*). To quantify the extent to which unobserved heterogeneity affects respondents' evaluations of reskilling, we turn to a mixed-logit model, which allows for random taste variation. We specify $f(\beta)$ to be continuous and distributed as a normal. The choice probability becomes:

$$P_{ij} = \int \left(\frac{e^{\beta x_{ij}}}{\sum_m e^{\beta x_{im}}} \right) \phi(\beta|b,\ W) d\beta \tag{2}$$

where b and W are the mean and the variance-covariance of the normal density $\phi(\beta|b,\ W)$. The fundamental difference with model 1 is that mixed logit, by allowing coefficients to be individual-specific, estimates different moments of the β distribution, allowing us to draw the entire distribution $f(\beta)$.

We derive the mixed logit probability through random coefficients, following the model:

$$U_{ij} = \sum_{k=1}^{K} \beta_{ik}\ X_{jk} + \varepsilon_{ij} \tag{3}$$

Equation 2 thus represents the probability of selecting alternative *j conditional* on parameters β_i. This specification allows us to estimate the whole distribution of WTPs across individuals. While this model relaxes the assumption of taste homogeneity, it also entails a loss of efficiency because we need to resort to numerical simulations to estimate the model.

Figure 9 shows the simulated WTP distribution by demographic groups. Panel (a) shows that

men's willingness to pay for reskilling is shifted to the right of women's distribution, in line with the average results shown in Figure 8a. However, the two distributions are also overlapping for most of the x-axis range. This confirms that gender, while being correlated with interest in reskilling, does not entirely account for differences in WTP. We find similar results also for age and education.

5.5 Summary

In this section we quantified respondents' willingness to pay for reskilling. Jobseekers are willing to pay for a reskilling program in IT, but need to be compensated to engage in reskilling as construction technicians, conditional on the same program design and job finding rate post-course. This highlights the importance of tailoring training policies (including subsidies) to specific occupational needs.

Additionally, we have shown that the WTP estimates for the same treatment occupation vary according to individuals' demographic characteristics and beliefs. This suggests that targeting segments of jobseekers more likely to have a positive WTP for the specific occupations (e.g. those who have a higher identity fit with the occupation) may increase the effectiveness of training policies.

Finally, we have shown that there is considerable heterogeneity in choices and even within groups of participants sharing the same demographic characteristics. This creates room to the possibility that reskilling intentions could be shaped by interventions that improve information on the returns to the treatment occupations, or that shape people's perceptions of their identity fit in new occupations. We explore this possibility in the next section.

6 Can the demand for reskilling be shaped?

In this section, we explore whether interest in reskilling may be shaped by light-touch policies that aim to address psychological and informational frictions by introducing two randomized treatments within our survey. We then examine the possible impact of policies providing monetary incentives for reskilling.

6.1 Encouraging reskilling through light-touch policies: a randomized experiment

6.1.1 Experimental Design

The evidence presented in section 4.2.2 showed that both psychological factors—e.g., one's occupational identity—and informational constraints—e.g., perceived returns to the treatment occupation—are correlated with training choices.

We now examine the impact of a light-touch intervention aimed at influencing these factors, which we implemented by randomizing respondents into the following three groups:

1. Information (INFO): we provide information on the level of vacancies and on the average wage in the treatment occupation. As shown in Figure 10a, we communicated to jobseekers 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).[46]

2. Role model and growth mindset (MINDSET): respondents are shown a "success story" of a woman who succeeded in reinventing herself after a training program and learn about the concept of "growth mindset" (see Figure 10b).

3. Control group (CONTROL): no additional information is provided before training choices.

Both the MINDSET and INFO treatments were administered through videos of a length of approximately one to two minutes. Both videos consisted of voice-over slides and had the same voice narrating the text. Viewers could skip the video but were asked some comprehension questions afterward. In case of a wrong answer, the survey would recommend them to watch the video again. We recorded the time spent watching the video, as well as the answers to comprehension questions. We randomized assignment to the three treatments within each gender-occupation cell (e.g., women-IT).

These treatments are used to study whether respondents change their reskilling intentions, in the survey, as well as their real-life behavior outside of the survey.

[46] For 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.

Balance Table A3 shows that assignment to treatment is balanced on observables. Column (1) shows the mean in the control group and Columns (2) and (3) the difference in each of the treatment groups. 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. Column (5) reports the p-value of the comparison between the two treatment groups. According to the F-tests, we find imbalances on 4 out of 28 variables, but differences are small in magnitude across treatments.

6.1.2 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, eg. 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 features of 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). 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, compared to the opt-out in choice scenario j.

Reskilling intentions Table 5 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 slightly larger for the IT occupation than the one in construction, but the difference between the two effects is not statistically significant. Columns (4) to (6) adjust the estimates to take into account respondents' limited attention to the intervention video. Column (4) excludes from the sample 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.[47] Reassuringly, independently of the adjustment for inattention, we find very similar—and slightly stronger—results for the effect of information provision.

Panel B of Table 5 shows that the information treatment does not change the likelihood that respondents choose any training course compared to the opt-out option. This confirms that the content of the informational video was correctly 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.

The second row of Panel A in Table 5 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 identity fit across occupations. This evidence resembles the results in Delfino (2024), which also show that an informational treatment is more effective than an identity-focused message to encourage men in caring sectors.

Given the positive average impact of information, a natural question is who benefits the most from it, and whether the effect is heterogeneous depending on baseline preferences and beliefs (Table 4). Table 6 explores heterogeneity in treatment effects by respondents' interest and beliefs about the treatment occupation. Columns (4) to (6) show that the effect of information is concentrated among respondents who underestimated the wage. By getting correct information about the (higher) wages in the treatment occupation, this group of jobseekers reacts by choosing to reskill more frequently. Columns (1) to (3) show heterogeneity by interest. Here we find that people in the lowest interest quartile do not react at all to information, which instead similarly affects choices in all the higher quartiles of the interest distribution. This suggests that there are at least 25% of our respondents who dislike the reskilling occupation and do not react at all to information about the potential labor market returns of engaging in it.[48]

Willingness to pay for reskilling So far, we investigated whether information increases the likelihood that respondents choose reskilling instead of other training, or no training at all. We now ask whether information also changes the value that respondents attach to reskilling, ie. their willingness to pay for it. We leverage again our discrete choice model to estimate the effects of the two treatments

[47] The survey showed again the video if a respondent did not reply correctly to one of the two understanding checks. The understanding checks asked about the statistics provided by the treatment video (for the INFO treatment) and about the meaning of growth mindset (for the MINDSET treatment).

[48] We also find no differences in the reaction to information by gender or by treatment occupation.

on the WTP for reskilling. Figure A6a shows that, similarly to the extensive margin results, the information treatment has a sizeable effect on WTP, while the Mindset treatment (Figure A6b) has no effect.

How big is the effect of information? To calibrate the magnitudes of the treatment effects, we quantify how much of the gap between female and male job-seekers we can close through the information treatment. Figure 11 shows that the treatment effect closes around 33% of the gap between male and female respondents at the median of the WTP distribution.

6.1.3 Impact on real-life training and job outcomes

We just saw that the information treatment is effective in changing reskilling intentions within our survey. Does the effect of this randomized treatment spill over into the participants' real-life choices?

In the administrative data from AFOL, we observe whether a participant engaged in any training (within the Lombardy region) from January 2022 to September 2024. The survey was administered between April and September 2023. From the training title, we can classify whether the course counts as reskilling (defined as a course devoted to learning how to perform a job) or generic training (a course whose topic is a soft skill or a skill that can be used in multiple jobs, e.g.: learning Microsoft Excel). Moreover, by looking at whether the course has a particular focus on an occupation in IT or construction, we can further classify reskilling related to our survey choices or not.

In addition to training behavior, the administrative data also contain information on job contracts, for which we have data from before the survey to September 2024. For each contract, we know the industrial sector. We use the NACE Rev.2 industrial classification and based on Eurostat data we define three categories of sectors: low Value Added, high Value Added, and IT.[49,50] The idea is to look at whether the knowledge acquired in the survey encouraged people to try and aim to find a job in sectors with higher returns, either linked to the information received (i.e., in IT) or not.

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

[49] The IT sector is defined as the sum of macro-industries M and J, i.e. the Professional, Scientific, and Technical service sector and the Information and Communication one. Eurostat defines many (11 out of 15) of the 2-digit industries in such macro sectors as "Knowledge Intensive Services", plenty of which are labeled as "High-Tech".

[50] We classify sectors being high or low value-added based on Eurostat data. We compute the average value-added in the last two available years (2021-22) and we define the top 4 sectors as high value-added.

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

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: reskilling aligned with the occupations shown in the survey, reskilling in occupations outside of the focus of the survey, generic training, any training. Our coefficient of interest, β, provides the differential change in the likelihood that i chooses a certain training option, e.g., reskilling within the survey occupations, in the information treatment compared to the control, after participating in the survey.

Given the important differences in respondents' willingness to reskill between IT and construction, we also explore whether there are downstream effects of the survey treatments in job search and choices depending on the occupation that we showed in the survey. We augment our previous model into a triple difference-in-difference, where we further interact the information treatment indicator and the $Post_s$ dummy with an indicator equal to one for being assigned to the IT treatment occupation $TOcc_i^{IT}$ in our survey (and zero for receiving the construction occupation):

$$y_{is} = \alpha + \beta\, T_i^{info} \cdot Post_s \cdot TOcc_i^{IT} + \gamma_1 Post_s + \gamma_2 Post_s \cdot TOcc_i^{IT} + \gamma_3 T_i^{info} \cdot Post_s + \gamma_i + \epsilon_{is}$$

Using this model, we look at the following outcomes: whether the jobseeker started any job, started a job in a low or high valued-added sector, or started a job in an IT sector. The key coefficient of interest is β, which shows the difference in the information average treatment effect between the IT and the Construction sectors. Essentially, β tells us whether individuals assigned to the IT treatment arm have a higher likelihood of finding a job (in a given sector) as a result of the information treatment than those in the Construction group.

Results Panel A of Table 8 shows the effect of our information treatment on training engagement after the survey, controlling for individual fixed effects, in comparison with the control group. Column (1) shows that there is a 0.03 percentage points increase in the likelihood that a participant engages in a reskilling program related to IT or construction after participating in our survey and receiving

the information treatment, compared to participants who did not receive any information within the survey. Columns (2) to (4) show that this effect is only limited to reskilling courses that are related to the topic of the survey. We find indeed no effect of the information treatment on reskilling in other occupations, on taking-up generic training or on a variable that considers engagement in any type of training (either reskilling or generic).

Panel B further shows that the results on engagement in survey-related reskilling are driven entirely by participants assigned to the IT treatment arm. This can be explained by either demand- or supply-side factors. On the demand side, survey participants showed stronger intentions to reskill in IT, which may have converted into a greater motivation to look for courses in their lives. Moreover, the relative vacancy rate communicated in the information treatment was ten times higher in IT compared to construction, potentially increasing the power of the intervention in this arm.[51] On the supply side, the offer of reskilling courses in Lombardy during the study period was much higher in IT compared to construction, making also access to reskilling in IT much easier.

Table 9 shows results on job outcomes. While the overall effect of the information treatment is muted, we find significant differences between our two sectors. Respondents assigned to the construction treatment are less likely to find any jobs, particularly so in the low value-added and IT sectors. On the other hand, the information treatment is more effective for the IT treatment arm: those in that group are more likely to find a job in any sector (column 1), with the difference being statistically significant only in the IT sectors (column 4).

6.2 Encouraging reskilling through governmental policies: simulations

6.2.1 Empirical motivation and design

One of the strengths of our framework is that, after having estimated preferences, it allows us to simulate agents' behavior in different hypothetical scenarios. In particular, we can estimate the participation rate of different training courses based on their features among different scenarios. We exploit this feature of our model and simulate the effects of a policy recently implemented by the Italian government (*Supporto per la formazione e il Lavoro, SFL*). The Support for training and work has been in place from September 1^{st} 2023 and provides for at most 12 months a cash transfer of €350 per calendar month to the eligible beneficiaries that take up any kind of training. The subsidy is

[51] Note however that we do not find differential effects of the information treatment on reskilling intentions between IT and construction in the survey.

arguably low for workers, amounting to 17% of the national average monthly income, but relatively high for the unemployed, representing 26% of the maximum unemployment benefit that they can get every month. Beneficiaries are those aged between 18 and 59 years old, with an annual value of household earnings and assets of at most €6,000.[52]

We study and predict participation rates in four hypothetical cases. In the first one, we try to approximate the Italian *status quo*: training features are set to be the average ones, but we assume job-seekers to be uninformed and omit the job finding rate. In the second case, we add to these features an unconditional subsidy granted for any training. The subsidy amounts to €350 per calendar month and is included in the model as a subsidy per hour of training. This case represents the scenario of a generic training subsidy. The third case compares the best reskilling program (in presence, intensive, 500 hours long, and with a 90% job finding rate) with the worst generic one (online, intensive, 80 hours long, and with a 23% job finding rate).[53] Here, we don't include the subsidy, and costs are set to be the average ones. This case represents the scenario of selection and information. Finally, our fourth case adds to the selection and information of a targeted subsidy. Programs' features will be the same as in the third case, but a subsidy of the same amount of the SFL is provided for those taking the reskilling training.

Using the parameters estimated in 1, we compute the indirect utility associated with each training. We then estimate the market share of each training as the ratio of the indirect utility of one program to the sum of the other indirect utilities.

$$PR_j = \frac{exp(V_j)}{exp(V_r) + exp(V_g) + exp(V_0)} \quad \text{for } j = \{r, g, 0\} \tag{4}$$

where PR_j is the participation in training j, V is the indirect utility of each program, r is the reskilling program, g is the generic training, and 0 is the opt-out option. The results of this exercise are presented in Figure 12a and 12b.

6.2.2 Impact on predicted reskilling take-up

The results show how the take-up rate of the reskilling program changes across different scenarios. In line with empirical evidence, in the adjusted baseline case the participation rate to reskilling pro-

[52] Assets holdings and earnings at the household level are measured in Italy through the Economic Equivalent Status Indicator (ISEE). This is widely requested by government authorities to provide subsidies and tax credit. The average ISEE in Italy is €15.327,57 in 2023.

[53] We provide a robustness check in which we compare the best reskilling program with the best generic one.

grams is low: most of the job-seekers prefer not to do any training, or to do a generic one. Inserting an unconditional subsidy into the picture slightly increases the take-up rate of both training programs: agents find less attractive the opt-out option because they can get some monetary compensation for their effort in training. However, providing job-seekers with information about their job finding rate after the training and with a selection of programs almost doubles the baseline participation rate to the reskilling program. In the final scenario, we add on this a subsidy granted to those who join a reskilling program: unsurprisingly, the participation rate increases by slightly more than 10 percentage points.

In line with the large differences in occupational preferences documented in the empirical section, we repeat this experiment separately by occupation. Results are shown in Figure 12b. Again, in the adjusted baseline scenario most of the people prefer not to do any training. Most notably, participation rates in reskilling and generic training are almost equivalent in the IT occupation. As in the pooled case, providing respondents with an unconditional subsidy does not revert the preference rank, since it only increases the take up rate in both types of training by the same amount (12% in Construction, 20% in IT). In the IT sector, however, the monetary incentive coupled with the more favorable preferences are sufficient to have equivalent shares between all three scenarios. Providing job-seekers with information about potential job finding rates doubles the reskilling share for both IT and construction occupations, leading to an increase in the reskilling share by more than 80%. Bundling together selection, information, and conditional monetary incentives (scenario 4) is the most effective policy combination to bring people into reskilling. In the IT occupation, the reskilling share reaches almost 70%, and almost 50% for construction.

These results provide suggestive evidence that light-touch cost-effective measures can increase the take up of reskilling programs.

7 Conclusion

Using data on Italian jobseekers, we show that demand-side barriers may prevent jobseekers from pursuing reskilling in high-demand occupations. We find striking differences in willingness to pay for reskilling across occupations. Within occupations interest in reskilling varies by gender and age. However, most of the variation in reskilling choices is explained by preferences and psychological factors, such as concerns related to professional identity, beliefs about the returns to reskilling, and

social status in high-demand occupations. The key message is that reskilling intentions are a) highly heterogeneous by occupation and b) not easy to predict based on data that are commonly available to job centers or policymakers.

Despite the challenges entailed in predicting reskilling, we also show that information provision about the labor market returns to reskilling may be a cost-effective way to stimulate program take-up. Two types of messages seem to be potentially effective: information about vacancies and monetary returns in high-demand occupations, or the effectiveness of reskilling programs in increasing the job finding rate among participants.

Our results are relevant beyond the Italian context. Everywhere in the world, training is an essential component of labor market policies. Yet, evidence on how to best match jobseekers to courses is lacking. This limits the information available to policymakers to target their workforce development strategies to those who are most likely to engage and benefit from them.

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8 Figures

Figure 1: Survey structure

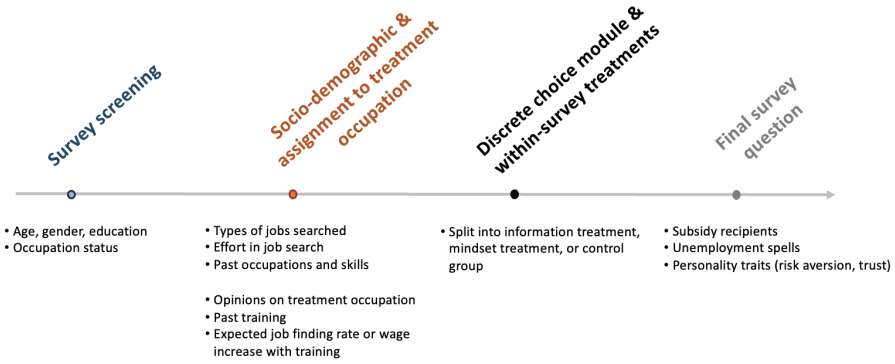


Figure 2: Between individual experimental treatments

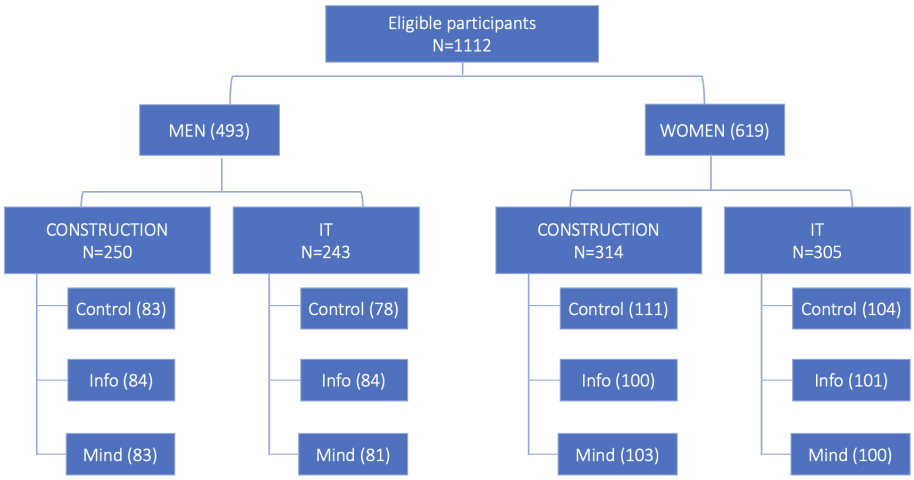
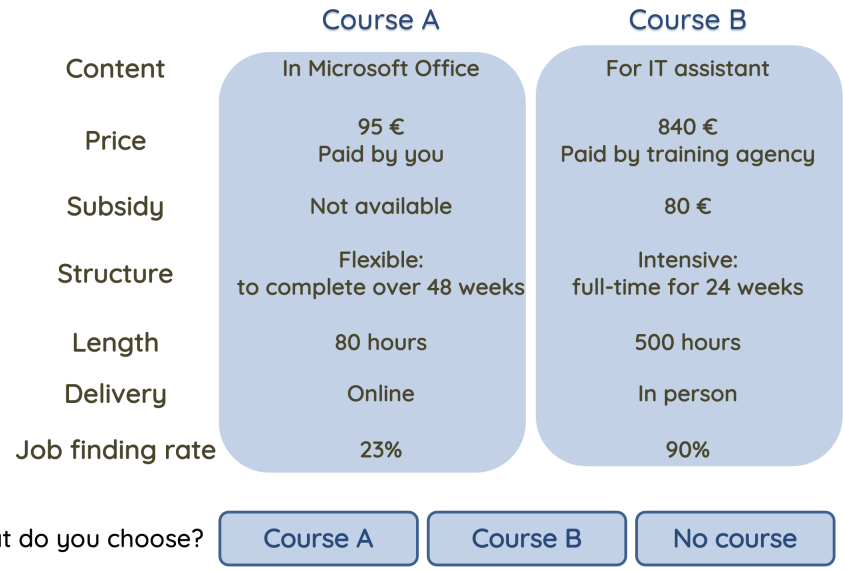
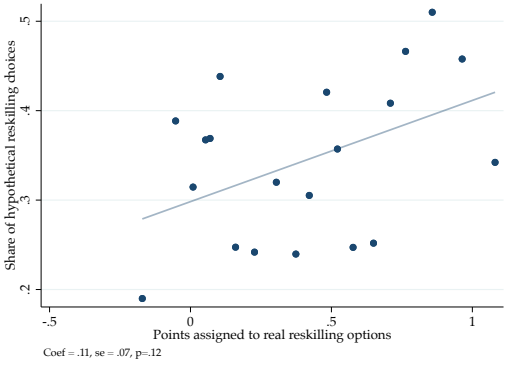


Figure 3: Example of binary training choice

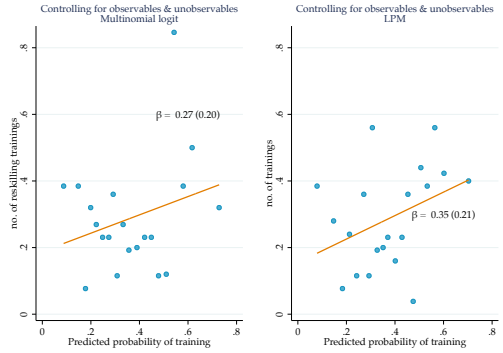


Note: the figure shows an example of a choice scenario from the discrete choice module of the survey. Each respondent saw six scenarios like this, with changing features.

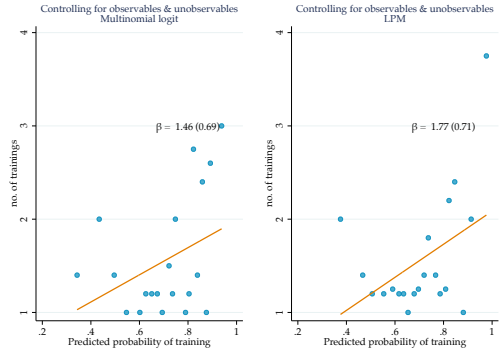
Figure 4: Survey choices and real behavior



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



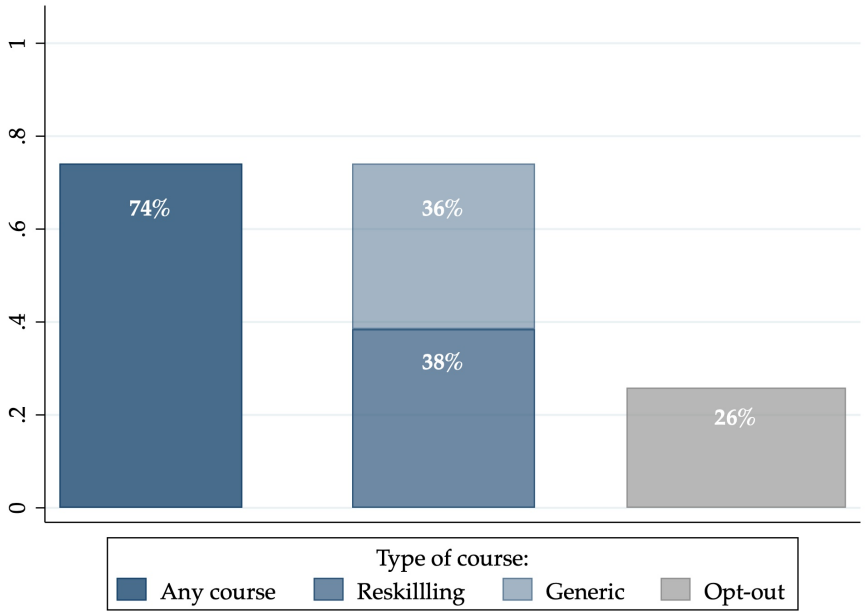
(b) Likelihood of choosing training and real behavior, extensive margin



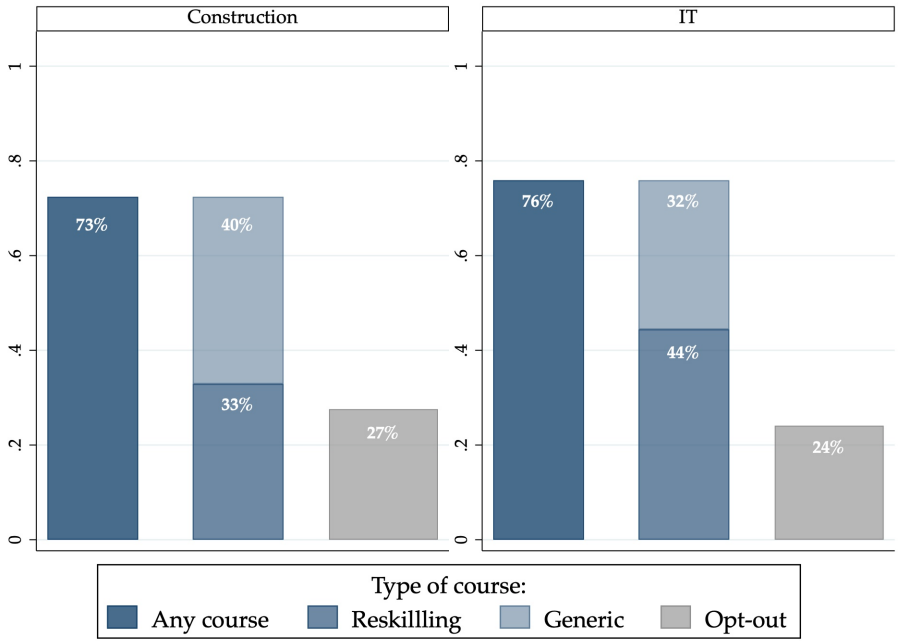
(c) Likelihood of choosing training and real behavior, intensive margin

Note: The figure shows two exercises that correlate choices in the survey with real behavior. 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 shown in Table A4. 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 5: Choice of different types of courses



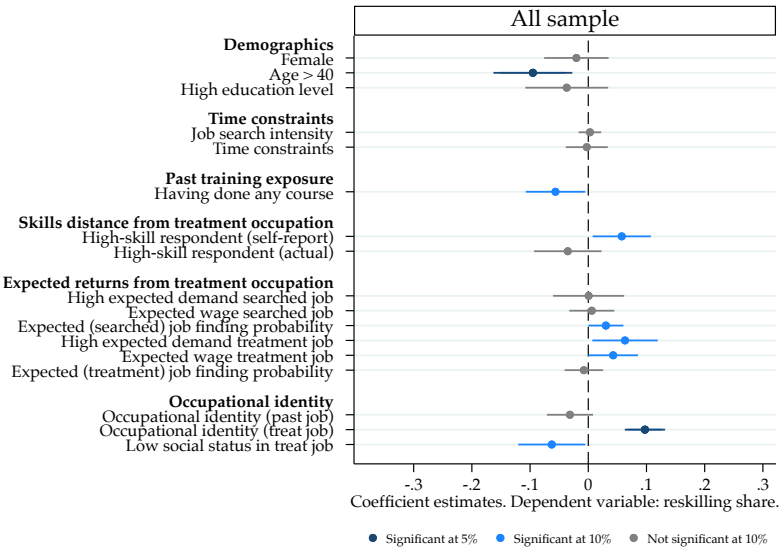
(a) Pooling treatment occupations



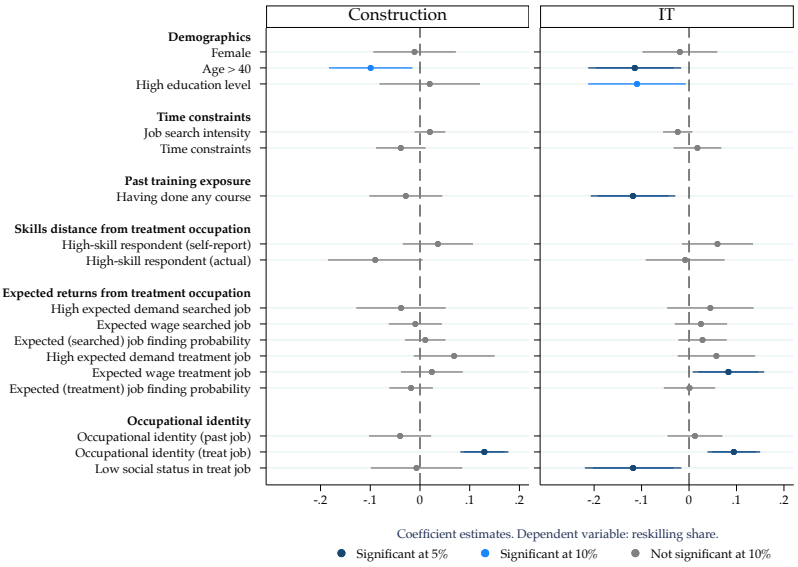
(b) By treatment occupation

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 by treatment occupation.

Figure 6: Individual correlates of reskilling intentions



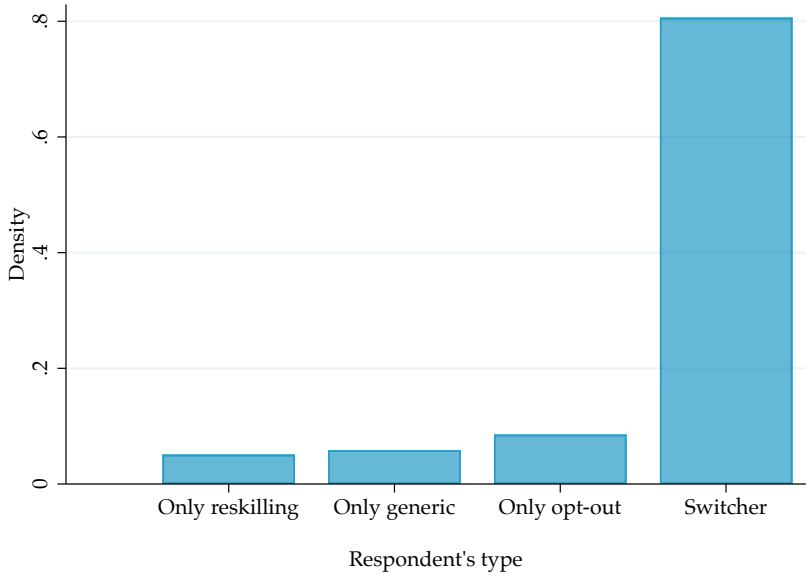
(a) Pooling treatment occupations



(b) By treatment occupation

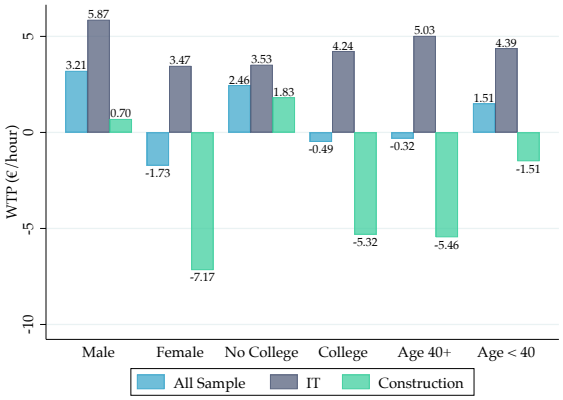
Note: The figure shows the coefficients of an OLS regression of reskilling frequency on all the displayed variables. The regression also controls for the region of residence, length of unemployment, past occupation dummy, survey sample, randomization block, and treatment occupation. 95% confidence intervals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

Figure 7: Respondents change their choices depending on course features



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

Figure 8: Willingness to Pay estimates for different groups



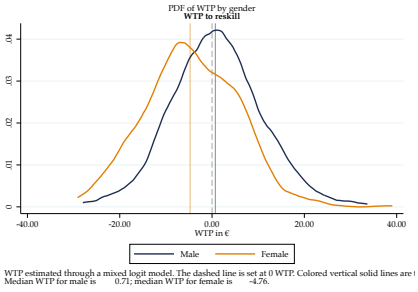
(a) Heterogeneity by demographics



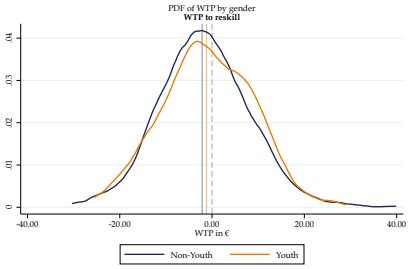
(b) Heterogeneity by treatment occupation, interest and beliefs

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 Equation 1.

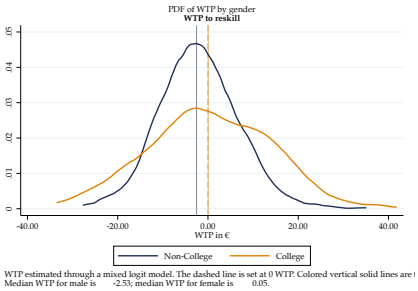
Figure 9: Willingness to Pay distributions for different groups



(a) WTP by gender



(b) WTP by age



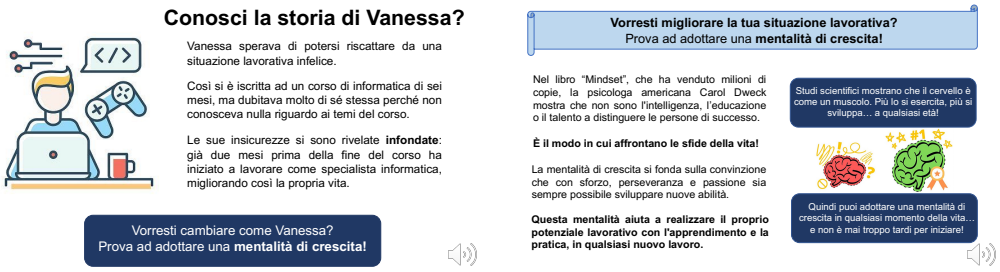
(c) WTP by education

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.

Figure 10: Experimental treatments



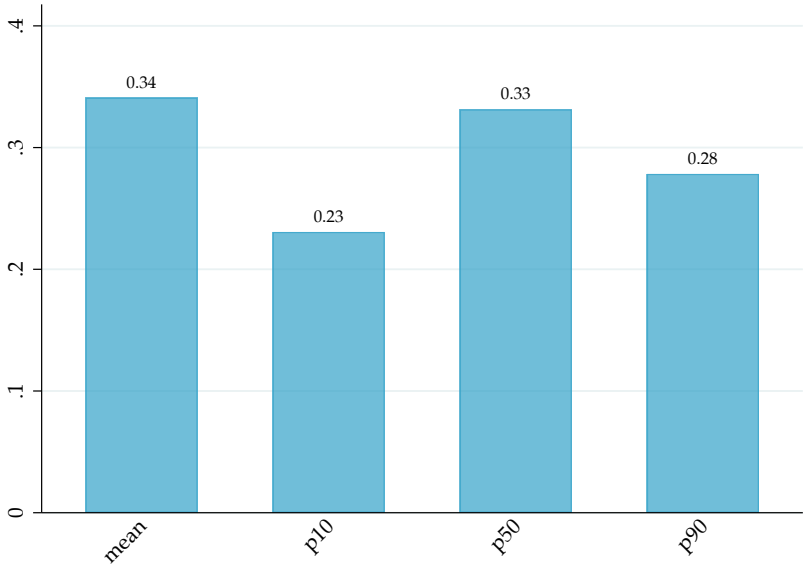
(a) Information treatment (IT occupation)



(b) Mindset treatment

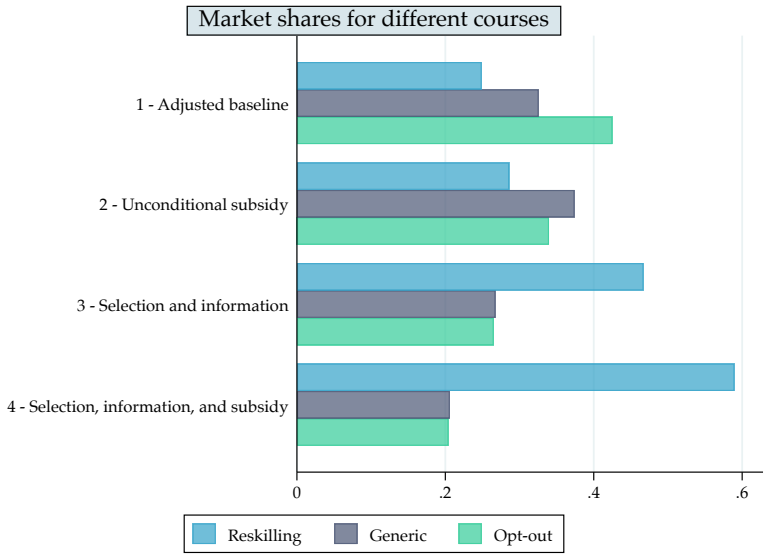
Note: the figure shows the main contents of the two experimental treatments. Figure (a) shows a screenshot of the information treatment video. The video showed first the information about the wage, while only after information about the vacancy rate appeared. For the survey company sample, we used data from Italy. For the survey with job center users, 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 occupation 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.

Figure 11: Benchmarking the treatment effect of information

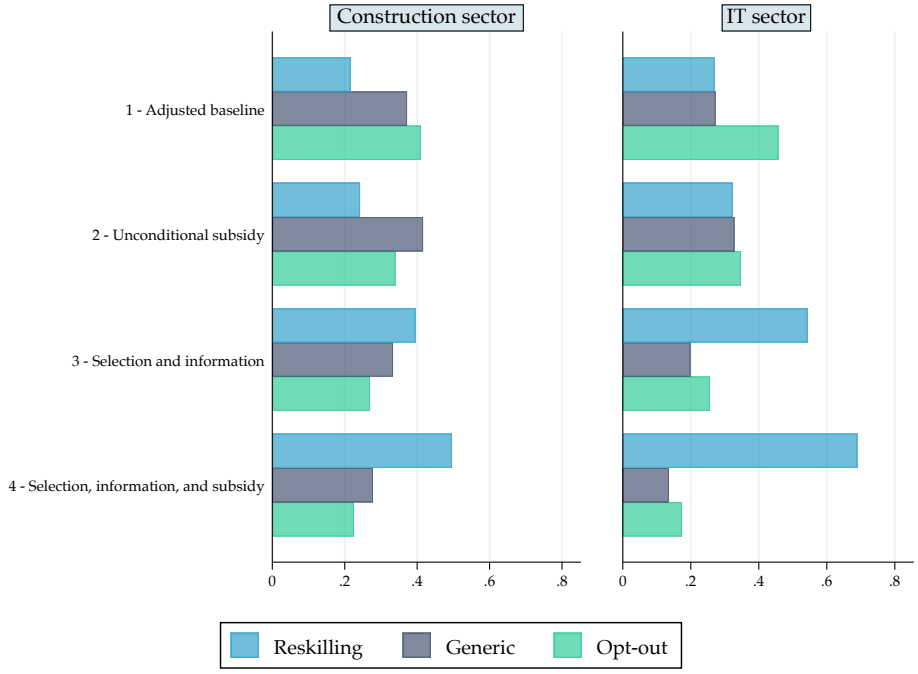


Note: the figure shows how much of the gap in willingness to pay for reskilling between female and male respondents is closed by the information treatment, at different points of the WTP distribution.

Figure 12: Predicted market shares for different hypothetical training programs in Italy



(a) Pooling treatment occupations



(b) By treatment occupations

Note: predicted market shares based on training features and estimated preferences. The different cases are detailed in the text.

9 Tables

Table 1: Descriptive statistics

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

Standard deviation in parentheses

Note: the table shows descriptive statistics for the sample, by gender.

Table 2: Marginal utilities for training features, control group

	(1) All sample	(2) Construction	(3) IT
Reskilling	0.030	–0.314**	0.371***
	(0.08)	(0.12)	(0.12)
Cost (€per hour)	–0.082***	–0.068***	–0.104***
	(0.01)	(0.02)	(0.02)
Job Finding Rate (%)	0.013***	0.012***	0.014***
	(0.00)	(0.00)	(0.00)
Duration (hours)	–0.001***	–0.000**	–0.001***
	(0.00)	(0.00)	(0.00)
Timing (1 if modular)	0.015	–0.056	0.096
	(0.05)	(0.07)	(0.08)
Delivery (1 if online)	–0.156***	–0.047	–0.279***
	(0.05)	(0.08)	(0.08)
Opt-Out	–0.191	–0.564***	0.230
	(0.15)	(0.21)	(0.22)
Constant	0.271	0.782	–0.466
	(.35)	(.51)	(.54)
Controls	Yes	Yes	Yes
N	6554	3366	3188
Pseudo R-squared	0.054	0.051	0.058

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

Table 3: WTP by treatment occupation

	(1) All sample	(2) Construction	(3) IT
Reskilling	.355	–7.333	3.735
	[–1.934, 2.443]	[–11.683, -.939]	[1.349, 7.229]
Job finding rate (%)	1.621	2.622	1.496
	[1.048, 2.393]	[.938, 3.973]	[.880, 2.466]
Duration (hours)	-.600	-.797	-.600
	[-.975, -.293]	[–1.587, -.059]	[–1.113, -.252]
Timing (1 if modular)	.227	-.999	1.022
	[-.784, 1.394]	[–3.117, 1.114]	[-.259, 2.700]
Delivery (1 if online)	–2.004	-.857	–2.850
	[–3.854, -.609]	[–3.780, 1.136]	[–5.489, -1.035]
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 4: Expectations about treatment occupations

	All			Females			Males		
Variable	Construction	IT	Diff	Construction	IT	Diff	Construction	IT	Diff
Identify with treat. job	3.76	5.03	1.26***	3.30	4.68	1.38***	4.35	5.47	1.12***
	(3.15)	(3.14)	(0.19)	(3.12)	(3.17)	(0.25)	(3.09)	(3.07)	(0.28)
Identification with past job	10.86	11.19	0.33	11.38	11.70	0.32	10.20	10.55	0.35
	(4.23)	(3.81)	(0.24)	(3.90)	(3.49)	(0.30)	(4.53)	(4.10)	(0.39)
Expected wage in treatment job	1073.44	936.55	-136.89***	1012.93	884.69	-128.24***	1149.44	1001.65	-147.79**
	(669.22)	(588.87)	(37.84)	(641.77)	(562.80)	(48.57)	(696.05)	(615.03)	(59.22)
Expected wage in treatment job w/ cert	1223.74	1077.07	-146.67***	1161.61	1030.84	-130.77**	1301.78	1135.10	-166.68**
	(801.87)	(686.56)	(44.82)	(794.71)	(658.34)	(58.75)	(805.59)	(717.59)	(68.78)
Expected wage in treatment job w/ course	1161.93	1033.26	-128.68***	1107.12	992.39	-114.73**	1230.78	1084.55	-146.23**
	(729.54)	(627.00)	(40.84)	(719.21)	(600.69)	(53.34)	(738.00)	(656.19)	(62.96)
Expected wage searched job (€)	1170.07	1144.48	-25.59	1101.73	1048.90	-52.83	1255.90	1264.44	8.55
	(734.22)	(741.46)	(44.25)	(531.92)	(610.83)	(46.00)	(921.93)	(864.84)	(80.56)
Expected wage searched job with course (€)	1187.62	1153.86	-33.75	1128.94	1058.21	-70.73	1261.32	1273.93	12.61
	(764.09)	(790.49)	(46.62)	(574.96)	(658.18)	(49.63)	(945.91)	(917.73)	(83.97)
Expected wage searched job with certified course (€)	1220.27	1175.95	-44.32	1155.37	1085.80	-69.57	1301.77	1289.09	-12.68
	(795.59)	(842.03)	(49.11)	(609.98)	(708.57)	(53.09)	(975.43)	(974.07)	(87.81)
High expected demand for treat. job	0.36	0.59	0.24***	0.34	0.62	0.28***	0.37	0.56	0.18***
	(0.48)	(0.49)	(0.03)	(0.48)	(0.49)	(0.04)	(0.48)	(0.50)	(0.04)
High expected demand for searched job (%)	0.47	0.42	-0.05	0.51	0.43	-0.08*	0.41	0.40	-0.01
	(0.50)	(0.49)	(0.03)	(0.50)	(0.50)	(0.04)	(0.49)	(0.49)	(0.05)
Probability to get the treatment job	31.42	39.79	8.36***	28.82	37.40	8.58***	34.70	42.79	8.09***
	(26.66)	(27.40)	(1.62)	(26.80)	(28.05)	(2.20)	(26.18)	(26.31)	(2.36)
Probability to get treatment job w/ course	46.27	54.57	8.30***	45.07	53.77	8.70***	47.77	55.57	7.80***
	(26.70)	(25.28)	(1.56)	(27.63)	(25.72)	(2.15)	(25.46)	(24.74)	(2.26)
Probability to get treatment job w/ cert	53.69	61.57	7.88***	52.71	61.40	8.69***	54.91	61.79	6.88***
	(27.61)	(25.82)	(1.60)	(28.78)	(26.32)	(2.22)	(26.06)	(25.23)	(2.31)
Probability to get the searched job	0.43	0.40	-0.03*	0.43	0.40	-0.03	0.44	0.42	-0.02
	(0.27)	(0.27)	(0.02)	(0.27)	(0.26)	(0.02)	(0.27)	(0.27)	(0.02)
Probability to get the searched job w/ course	0.55	0.53	-0.02	0.55	0.53	-0.03	0.55	0.53	-0.02
	(0.28)	(0.27)	(0.02)	(0.28)	(0.27)	(0.02)	(0.28)	(0.27)	(0.02)
Probability to get the searched job w/ cert	0.63	0.61	-0.02	0.63	0.61	-0.02	0.62	0.61	-0.01
	(0.28)	(0.27)	(0.02)	(0.28)	(0.27)	(0.02)	(0.27)	(0.27)	(0.02)
Interest in treat. job (0 to 10)	4.19	5.63	1.45***	3.74	5.33	1.59***	4.74	6.01	1.26***
	(3.29)	(3.20)	(0.19)	(3.35)	(3.28)	(0.27)	(3.14)	(3.05)	(0.28)
Confident can do treat. job (0 to 10)	3.82	5.22	1.40***	3.39	4.70	1.32***	4.36	5.86	1.50***
	(3.11)	(3.10)	(0.19)	(3.13)	(3.06)	(0.25)	(3.01)	(3.03)	(0.27)
Skills required for treat. occ. used in previous job (%)	0.71	0.66	-0.05***	0.72	0.70	-0.02	0.70	0.61	-0.09***
	(0.28)	(0.29)	(0.02)	(0.26)	(0.26)	(0.02)	(0.30)	(0.31)	(0.03)
Treat jobs suit better to men (%)	0.43	0.20	-0.22***	0.44	0.16	-0.28***	0.41	0.26	-0.15***
	(0.49)	(0.40)	(0.03)	(0.50)	(0.36)	(0.04)	(0.49)	(0.44)	(0.04)
Housework fullfilling for women (%)	0.31	0.29	-0.02	0.29	0.28	-0.01	0.33	0.30	-0.04
	(0.46)	(0.45)	(0.03)	(0.45)	(0.45)	(0.04)	(0.47)	(0.46)	(0.04)
Treat job associated to low social status (%)	0.27	0.19	-0.08***	0.25	0.17	-0.07**	0.31	0.22	-0.09**
	(0.45)	(0.39)	(0.03)	(0.43)	(0.38)	(0.03)	(0.46)	(0.41)	(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. "Identification with the job" asks respondent the extent to which they think that the job fits well with their identity. Both expected wage and hiring likelihood were asked in three scenarios: without doing any course, after doing a course, and after doing 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).

Table 5: The effect of information on reskilling choices

	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	0.044**	0.053*	0.035	0.048**	0.049**	0.056**
	(0.020)	(0.028)	(0.028)	(0.020)	(0.021)	(0.024)
Mindset Treat	0.003	0.007	0.001	0.022	0.017	0.005
	(0.020)	(0.029)	(0.028)	(0.022)	(0.022)	(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	0.022	-0.031	-0.006	-0.001	-0.016
	(0.023)	(0.031)	(0.034)	(0.024)	(0.025)	(0.028)
Mindset Treat	-0.008	-0.035	0.027	-0.002	0.006	-0.010
	(0.023)	(0.032)	(0.032)	(0.024)	(0.024)	(0.023)
Mean DV	0.735	0.742	0.728	0.738	0.742	0.735
Observations	6672	3288	3384	5826	5754	6672

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). 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 10^{th} and the 90^{th} 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.

Table 6: Heterogeneity in the effect of information on reskilling choices

	By interest			By priors		
	(1)	(2)	(3)	(4)	(5)	(6)
	Low interest	Mid interest	High interest	Exp w $<$ w	Exp w $\geq$ w	Uncertain
Information Treat	0.022	0.066*	0.104**	0.112***	-0.009	-0.013
	(0.05)	(0.04)	(0.05)	(0.03)	(0.05)	(0.06)
Mindset Treat	0.007	0.004	0.025	0.013	-0.018	0.013
	(0.04)	(0.03)	(0.05)	(0.03)	(0.04)	(0.05)
N	1668	3336	1668	3828	1530	1314
Mean DV	0.33	0.40	0.47	0.43	0.40	0.33
Info: (1)=(2) / (4)=(5) p			.28			.01
Info: (1)=(3) / (4)=(6) p			.1			0
Mindset: (1)=(2) / (4)=(5) p			.62			.51
Mindset: (1)=(3) / (4)=(6) p			.53			.85

Standard errors in parentheses

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

Note: The table shows heterogeneity in treatment effects by respondents' attitudes and beliefs about the treatment occupation. Columns (1) to (3) split the sample into three groups: respondents in the first quartile (Column (1)), between the second and third (Column (2)), or in the fourth quartile (Column (4)) of interest in the treatment occupation. Columns (4) to (6) split the sample by beliefs on wages in the treatment occupation. Column (4) estimates treatment effects on respondents who underestimate the wage, Column (5) on those who are correct or overestimate the wage, and Column (6) on those who did not report any expected wage. Standard errors are clustered at the individual level.

Table 7: Summary table from administrative data.

	All Sample		Control pre-post		Post survey		Control post	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Reskilling (survey)	.016	.124	.017	.13	.012	.107	.006	.076
Reskilling (out of survey)	.138	.345	.154	.362	.062	.242	.086	.281
Generic Training	.134	.341	.16	.368	.07	.255	.08	.272
Total Training	.239	.427	.263	.441	.12	.326	.143	.351
All Sectors	.685	.465	.674	.47	.571	.495	.583	.495
High-VA Sector	.324	.469	.326	.47	.25	.434	.246	.432
Low-VA Sector	.511	.5	.52	.501	.394	.489	.423	.495
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 outcomes in Tables 8 and 9. All Sample: pre and post survey. Control (1): Pre and post survey, control group only. Post Survey: post survey only, all treatments. Control (2): post survey and control group only.

Table 8: The effect of information on actual reskilling take up

Panel A: All treatment occupations

	(1) Reskilling (survey)	(2) Reskilling (out of survey)	(3) Generic	(4) Total training
Post	-0.006	0.011	-0.017	-0.006
	(0.010)	(0.029)	(0.029)	(0.037)
Post × Info	0.029*	-0.057	0.029	-0.029
	(0.015)	(0.040)	(0.038)	(0.051)
Constant	0.006	0.083***	0.077***	0.146***
	(0.004)	(0.010)	(0.010)	(0.013)
N	700	700	700	700
R-squared	0.50	0.48	0.54	0.52

Panel B: IT treatment only

	(1) Reskilling (survey)	(2) Reskilling (out of survey)	(3) Generic	(4) Total training
Post	-0.024	0.012	-0.048	-0.024
	(0.017)	(0.027)	(0.033)	(0.041)
Post × Treat	0.035*	-0.000	0.059	0.035
	(0.020)	(0.041)	(0.051)	(0.061)
Constant	0.012**	0.029***	0.076***	0.094***
	(0.005)	(0.010)	(0.013)	(0.015)
N	340	340	340	340
R-squared	0.51	0.48	0.56	0.52

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

Note: Clustered standard errors in parentheses. Comparison between the Information treatment group and the pure control. Post is a dummy variable indicating the time after completion of the survey. Treat is a dummy equal to one if the individual was treated with the information treatment. All regressions include individual FE and SE are clustered at the individual level. The outcome variables are dummies indicating whether an individual took up a reskilling training in digital topics (1), a reskilling training in topics different from the ones proposed in the survey (e.g.: logistics) (2), a generic training (3), or any training (4).

Table 9: Treatment effect on jobs started. Heterogeneity by occupation treatment (triple DID).

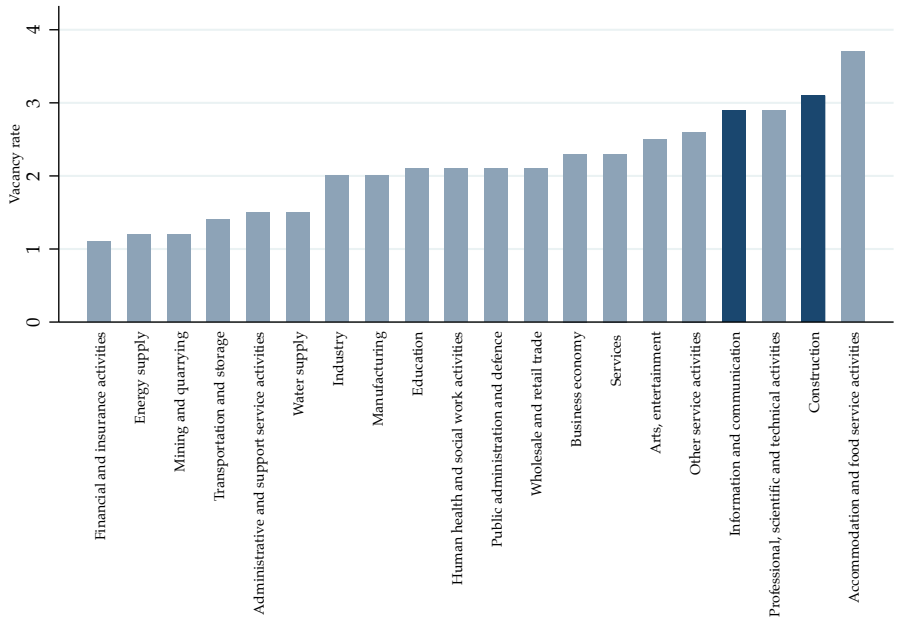
	(1) All Jobs	(2) Low VA sector	(3) High VA sector	(4) IT sectors
Post	0.407***	0.253***	0.165***	0.154***
	(0.073)	(0.069)	(0.055)	(0.044)
Post × Info	-0.193*	-0.197**	-0.030	-0.109*
	(0.110)	(0.100)	(0.084)	(0.059)
Post × IT	0.010	0.069	-0.034	-0.142**
	(0.098)	(0.095)	(0.081)	(0.057)
Post × Info × IT	0.242*	0.131	0.155	0.237***
	(0.146)	(0.137)	(0.118)	(0.080)
Constant	0.191***	0.163***	0.089***	0.034***
	(0.018)	(0.017)	(0.015)	(0.010)
N	700	700	700	700
R-squared	0.51	0.49	0.48	0.52

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Clustered standard errors in parentheses. Comparison between the Information treatment group and the pure control. Post is a dummy variable indicating the time after completion of the survey. Treat is a dummy equal to one if the individual was treated with the information treatment. IT is a dummy indicating the IT treatment arm. All regressions include individual FE and SE are clustered at the individual level.
The outcome variables are dummies indicating whether an individual took up any job (1), a job in the Low Value added sectors (2), in the High Value Added Sector (3), or in the IT sectors (4). High/Low Value added sectors classified based on Eurostat (*sbs_sc_ovw*) data: high value added sectors are the top four sectors in Italy (average between 2021-2022).
High Value Added sectors: Manufacturing; Construction; Wholesale and Retail Trade; and Professional, Scientific, and Technical activities.
IT sectors: Information & Communication; Professional, Scientific, and Technical activities.

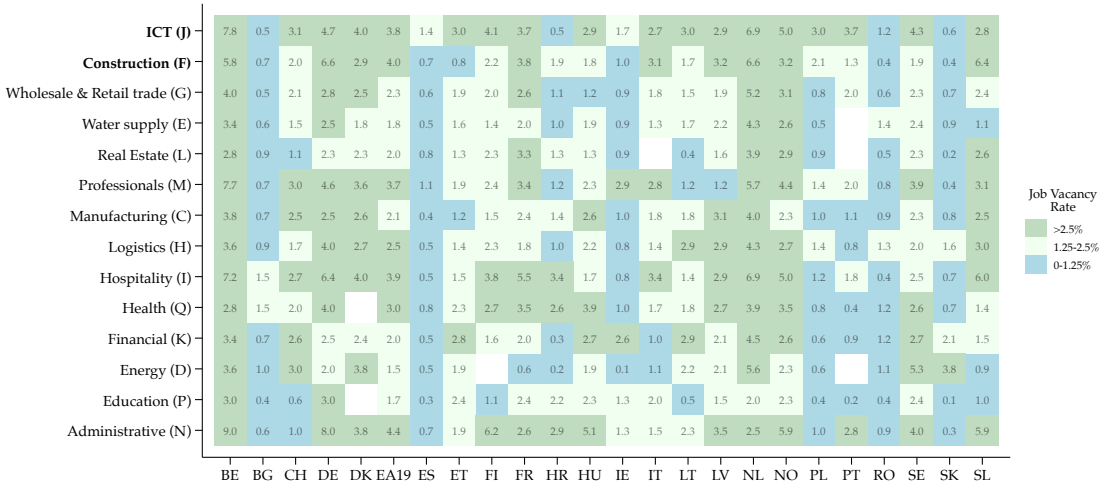
A Appendix Figures and Tables

Figure A1: Vacancy rate by industry in Italy



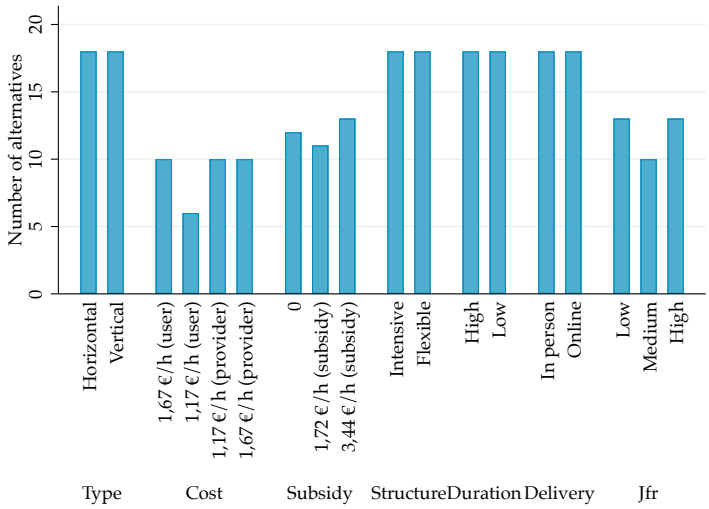
Note: The figure shows the vacancy rate in different sectors of the Italian labor market. Source: Istat, 2023

Figure A2: Vacancy rate by industry in Europe



Note: Job vacancy rate (2021-22 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 A3: Balance between factors in discrete choice module



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 A4: Factor levels in discrete choice module

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.

Table A1: Descriptive statistics by sample

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

sd in parentheses

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

Table A2: Jobcenter sample selection

	Jobcenter sample			Diff 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		44,224	512		

Education level not available for initial sample

Note: the table shows the comparison between the overall population of job centers in Lombardy, the initial job center sample that got the invitation to complete the survey, and the final job center sample with complete responses to the survey

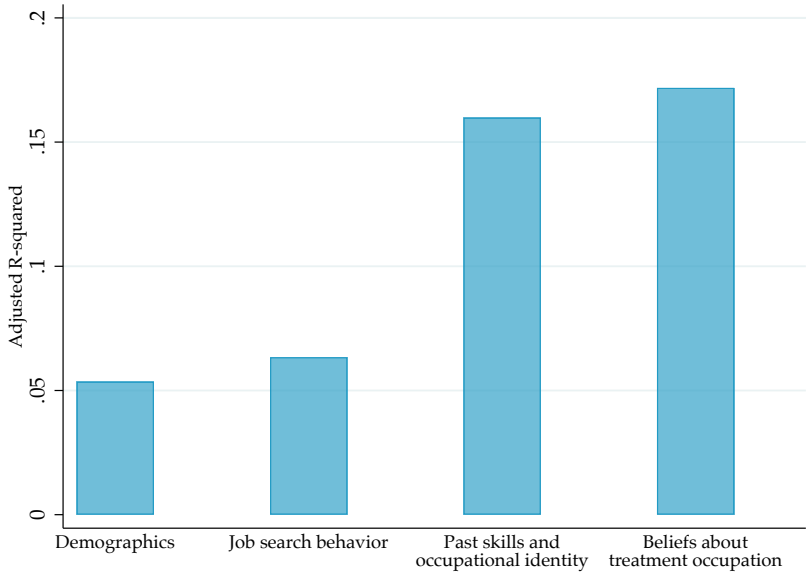
Table A3: Balance table

	Control	Info	Mindset	F-test	pairwise p
PANEL A: DEMOGRAPHICS					
Age (years)	40.449	-0.780	1.086	0.024	0.007
	(9.595)				
Region					
North (%)	0.641	-0.013	-0.018	0.773	0.869
	(0.480)				
Centre (%)	0.088	0.003	-0.000	0.980	0.857
	(0.283)				
South (%)	0.271	0.010	0.018	0.806	0.774
	(0.445)				
Has a partner (%)	0.469	0.013	0.030	0.717	0.648
	(0.500)				
Number of kids	0.604	-0.055	0.100	0.049	0.015
	(0.876)				
Time spent on household chores (hours)	3.343	-0.073	0.094	0.458	0.213
	(1.887)				
PANEL B: EDUCATION AND WORK EXPERIENCE					
Education					
Middle School	0.157	0.004	0.009	0.948	0.857
	(0.364)				
High School	0.612	-0.083	-0.079	0.034	0.907
	(0.488)				
College	0.221	0.077	0.075	0.025	0.962
	(0.415)				
Worked in the past (%)	0.941	-0.015	-0.005	0.697	0.590
	(0.235)				
Search past jobs (%)	0.571	-0.096	0.004	0.012	0.008
	(0.496)				
Skills required for treat. occ. used in previous job (%)	0.693	-0.010	-0.012	0.814	0.911
	(0.268)				
PANEL C: UNEMPLOYMENT					
Time unemployed after studying (months)	31.811	-3.319	-2.302	0.770	0.830
	(73.887)				
Time unemployed after kids (months)	24.979	8.616	1.061	0.239	0.170
	(40.472)				
Lenght of unemployment (months)	40.173	2.148	-1.627	0.690	0.391
	(53.909)				
Receives any subsidy (%)	0.383	0.039	0.045	0.314	0.854
	(0.487)				
Search other jobs (%)	0.734	0.003	-0.014	0.855	0.604
	(0.442)				
Number of jobs searched	2.947	-0.048	-0.008	0.914	0.742
	(1.663)				
Willing to accept other jobs (%)	0.910	-0.035	-0.013	0.296	0.338
	(0.287)				
PANEL D: TRAINING EXPERIENCE					
Done any course (%)	0.545	0.003	0.010	0.962	0.855
	(0.499)				
Usefullness of course (0-10)	7.380	-0.354	-0.051	0.372	0.266
	(2.841)				
PANEL E: EXPECTATIONS ABOUT JOB SEARCH					
Expected hiring probability for searched job (0-100%)	0.416	-0.012	0.019	0.278	0.112
	(0.267)				
Expected increment of hiring probability for searched job with course (0-100%)	0.130	-0.001	-0.017	0.241	0.153
	(0.177)				
Expected increment of hiring probability for searched job with certified course	0.073	0.012	-0.006	0.045	0.014
	(0.103)				
Expected wage searched job (€)	1140.681	-4.465	47.832	0.551	0.325
	(582.934)				
Expected wage searched job with course (€)	1161.112	-46.137	69.442	0.119	0.041
	(635.024)				
Expected wage searched job with certified course (€)	1196.856	-59.543	57.979	0.143	0.049
	(699.461)				
High expected demand for searched job (%)	0.462	-0.071	0.006	0.076	0.041
	(0.499)				
Confidence in being able to do searched job (0-10)	7.625	0.046	0.195	0.648	0.479
	(1.897)				
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). 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, and Column (5) the p-value of the comparison between the two treatments.

Figure A5: Explaining reskilling frequency with survey variables: adjusted R-squared



Note: The figure shows the adjusted R-squared of a regression of the frequency of reskilling choices on objective and subjective factors. The coefficients of this regression are shown in Figure 6a.

Table A4: Multinomial logit: marginal effects

	Model 1		Model 2		Model 3		Model 4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Generic training	Reskilling	Generic training	Reskilling	Generic training	Reskilling	Generic training	Reskilling
Gender	0.054	-0.290	0.001	-0.310	0.033	-0.119	0.019	-0.083
	(0.21)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.23)	(0.22)
Age > 40	-0.286	-0.652**	-0.238	-0.619**	-0.272	-0.683**	-0.250	-0.677**
	(0.21)	(0.22)	(0.22)	(0.23)	(0.22)	(0.23)	(0.22)	(0.23)
More than high school	-0.193	-0.222	-0.140	-0.202	-0.123	-0.230	-0.066	-0.204
	(0.25)	(0.27)	(0.26)	(0.27)	(0.26)	(0.26)	(0.26)	(0.27)
Intensity of job search	0.023	0.048	0.025	0.044	0.024	0.045	0.007	0.025
	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)
Ever done a training course	0.246	0.007	0.265	0.013	0.290	-0.049	0.221	-0.123
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
Index of time constraints	0.049	0.135	0.067	0.144	-0.003	0.001	-0.026	-0.055
	(0.13)	(0.14)	(0.13)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
High exp demand for searched job			0.067	0.197	0.067	0.159	0.062	0.126
			(0.23)	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)
Exp wage searched job			-0.188	-0.062	-0.172	-0.003	-0.044	0.029
			(0.13)	(0.15)	(0.13)	(0.13)	(0.14)	(0.15)
High-skill respondent (self-report)					-0.181	0.169	-0.195	0.175
					(0.20)	(0.21)	(0.21)	(0.20)
High-skill respondent (actual)					-0.175	-0.245	-0.152	-0.232
					(0.26)	(0.28)	(0.26)	(0.28)
Identification in past job					0.172	-0.032	0.200	-0.011
					(0.16)	(0.16)	(0.16)	(0.16)
Identification in treeatment job					0.163	0.552***	0.154	0.543***
					(0.10)	(0.10)	(0.10)	(0.10)
High exp demand for treat job							0.491*	0.547**
							(0.20)	(0.21)
Exp wage treatment job							-0.267	0.043
							(0.20)	(0.19)
Treat job associated to low social status (%)							-0.283	-0.480*
							(0.23)	(0.24)
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

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

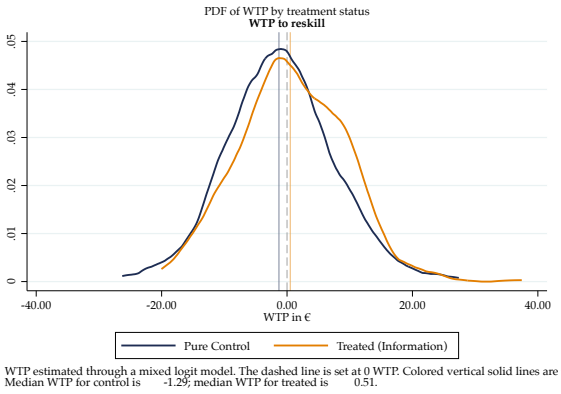
Note: The table shows estimates from a multinomial logit, where the choice of each type of course (generic vs reskilling) is compared to the choice of the opt-out. Table coefficients show marginal effects, in odd columns for the choice of generic training and in even columns for the choice of reskilling. *Intensity of job search* is the standardized ratio of the hours of job dedicated and the job search and the number of jobs searched. *Index of time constraints* combines standardized measures of the time individuals report spending on household chores and the standardized number of kids. *Self-reported share of skills for target job* is the standardized share of skills for treatment jobs that participants report to possess from their past occupation. *Actual share of skills for target job* is the standardized share of skills for treatment jobs that participants possess according to the O^*Net classification of their past jobs. *Occupational identity (past job)* and *Occupational identity (treat job)* are composite measures designed to capture the degree of identification individuals have with their part occupation and treatment occupation assigned to them. Both indexes are calculated by averaging the standardized level of personal identification individuals have with their current occupation or treatment occupation. *Expected wages* are constructed by multiplying pairs of related variables to capture the expected wage under different scenarios. Specifically, *Expected wage search job* represents the expected wage for a searched job, calculated as the product of the expected wage for a job and the expected probability of getting the searched job. *Expected wage search job with course* represents the expected wage for a searched job involving courses or certifications, derived from the expected wage for a job after a course and the expected probability of getting that same job with a course or certification. Similarly, expected wages for treatment occupations are constructed.

Table A5: Test of equality between Generic Training and Reskilling in Table A4.

	Model 1	Model 2	Model 3	Model 4
Gender	[0.039]	[0.062]	[0.355]	[0.537]
Age $>$ 40	[0.026]	[0.022]	[0.014]	[0.010]
More than high school	[0.895]	[0.777]	[0.610]	[0.513]
Intensity of job search	[0.663]	[0.739]	[0.728]	[0.759]
Ever done a training course	[0.100]	[0.082]	[0.020]	[0.020]
Index of time constraints	[0.375]	[0.428]	[0.966]	[0.769]
High exp demand for searched job		[0.442]	[0.579]	[0.698]
Exp wage searched job		[0.273]	[0.103]	[0.494]
High-skill respondent (self-report)			[0.017]	[0.011]
High-skill respondent (actual)			[0.723]	[0.680]
Identification in past job			[0.079]	[0.065]
Identification in treatment job			[0.000]	[0.000]
High exp demand for treat job				[0.722]
Exp wage treatment job				[0.015]
Treat job associated to low social status (%)				[0.230]

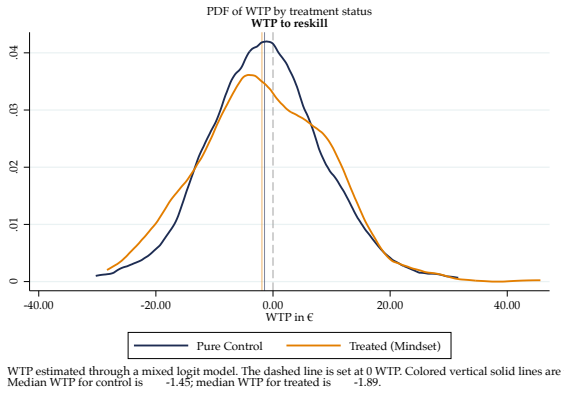
Notes: the table reports the p-value of a standard test of equality between coefficients of the multinomial logit model. Model 1 compares coefficients between columns (1) and (2) in Table A4; Model 2 compares coefficients between columns (3) and (4); Model 3 compares coefficients between columns (5) and (6); Model 4 compares coefficients between columns (7) and (8).

(a) Information treatment effect on the WTP for reskilling



WTP estimated through a mixed logit model. The dashed line is set at 0 WTP. Colored vertical solid lines are
Median WTP for control is -1.29; median WTP for treated is 0.51.

(b) Mindset treatment effect on the WTP for reskilling



WTP estimated through a mixed logit model. The dashed line is set at 0 WTP. Colored vertical solid lines are
Median WTP for control is -1.45; median WTP for treated is -1.89.

Figure A6: Experimental treatment effects on WTP for reskilling

Note: the figure shows the distribution of WTP estimates for reskilling by treatment status.

Table A6: Comparison between survey sample and Italian administrative data on the unemployed

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

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

Note: The table shows the unemployment features of people in job centers sample and survey company sample, and National data on the unemployed population. Data for both unemployed and inactive individuals are reported only for the length of unemployment and the percentage of individuals receiving subsidies. Source: Labor Force Survey, Italy.

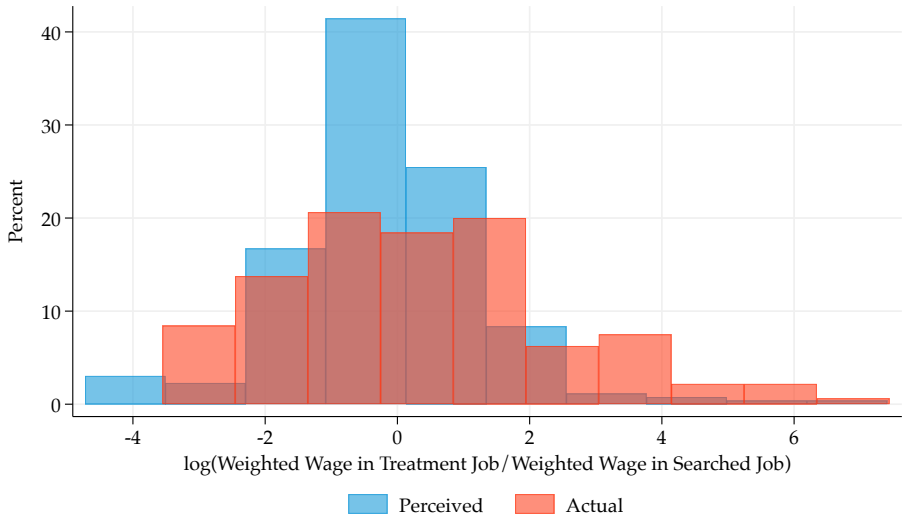
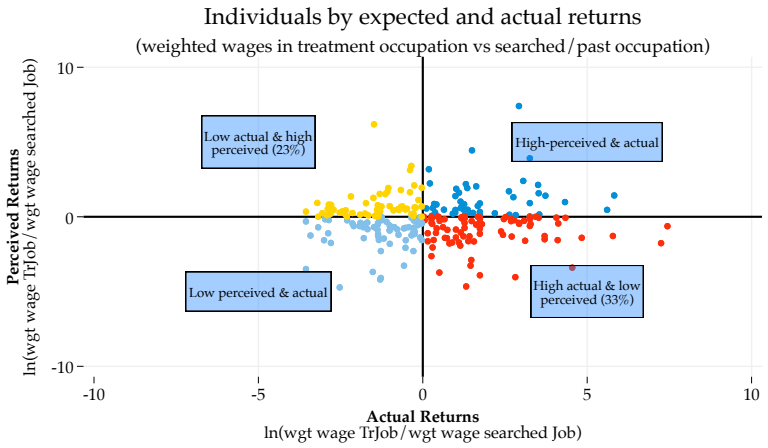


Figure A8: Perceived and actual returns distribution

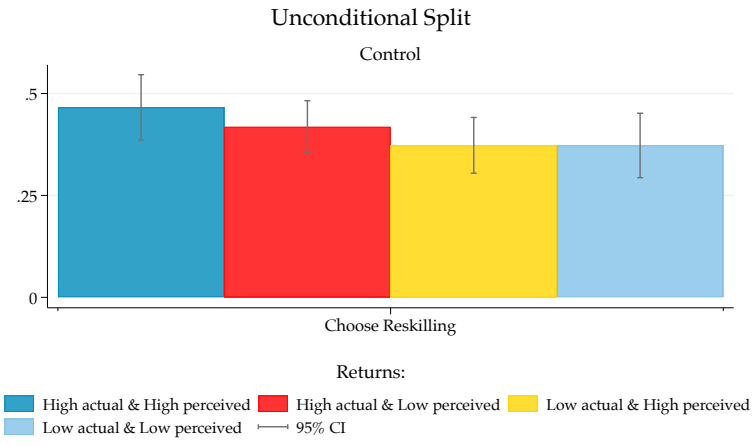
Note: The figure shows the comparison between our measures of actual and perceived returns from reskilling.

Figure A9: Returns: perceived vs average actual

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



(b) Perceived vs actual returns



Note:

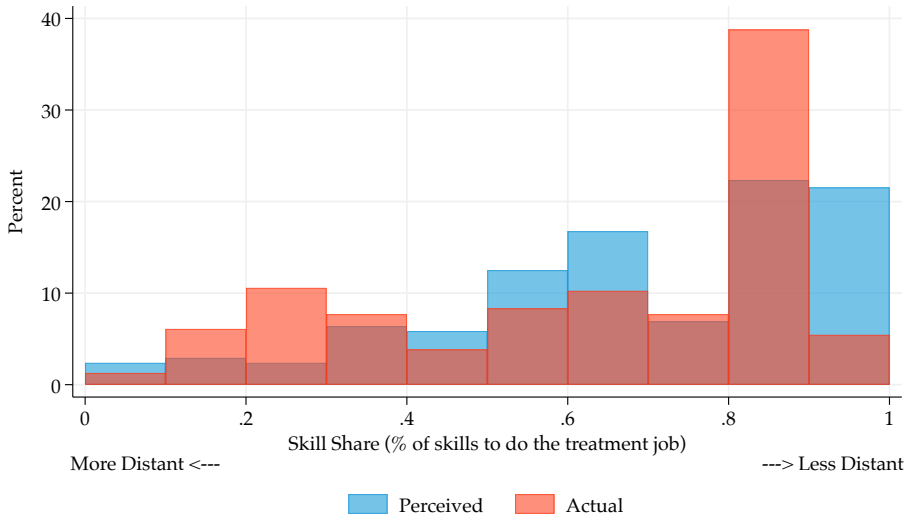
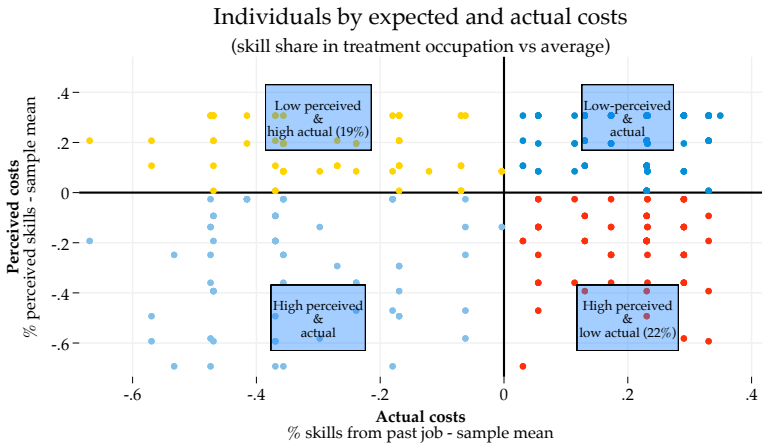


Figure A10: Perceived and actual cost distribution

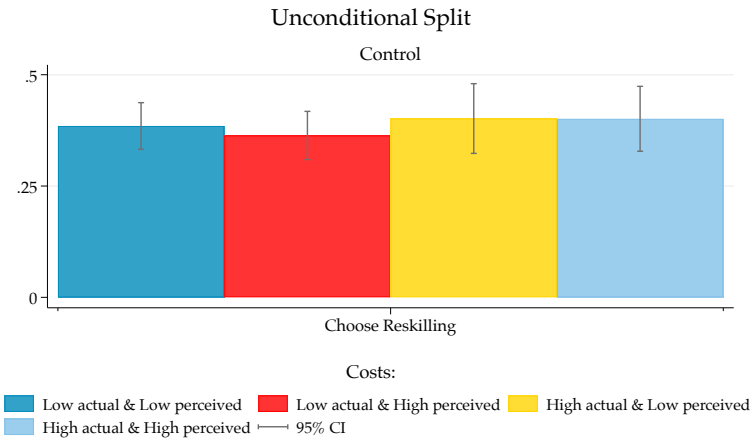
Note: The figure shows the comparison between our measures of actual and perceived skill distance from the treatment occupation. The actual distance comes from the previous occupation skill share (ONET data).

Figure A11: Costs: perceived vs average actual

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



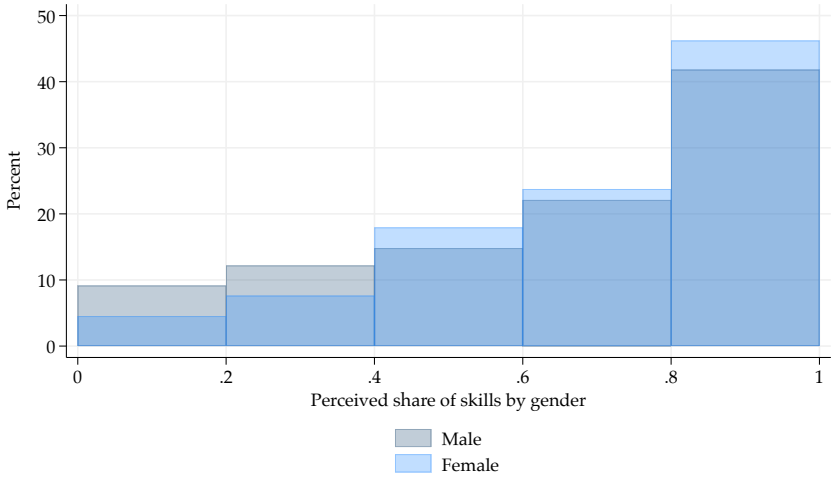
(b) Reskilling by quadrant of perceived/actual costs



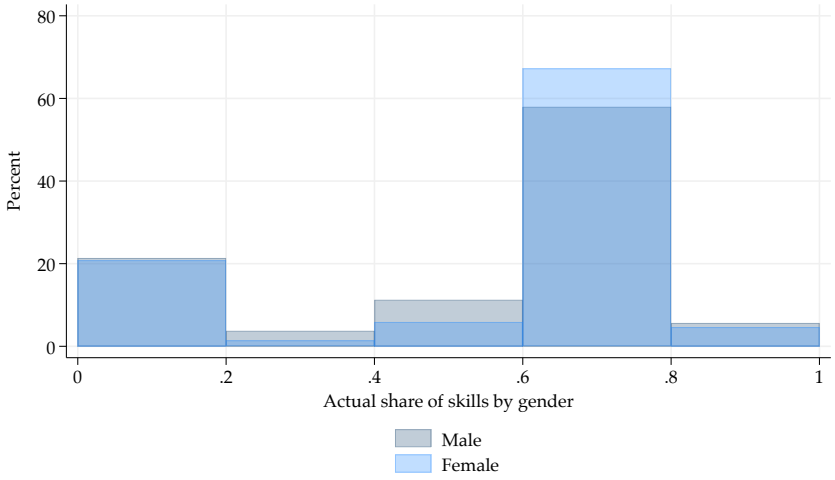
Note:

Figure A12: Skill distance from treatment occupations by gender

(a) Perceived distance



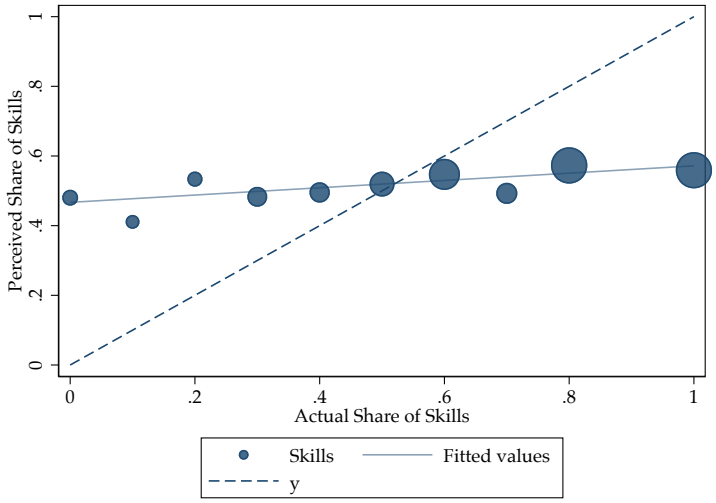
(b) Actual distance



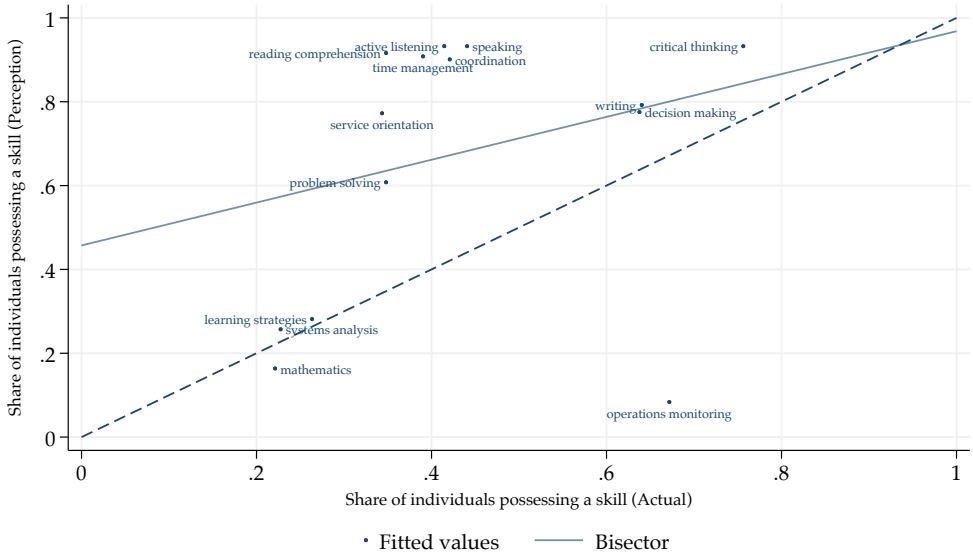
Note: The figure shows measures of skill distances between the past job performed by a respondent and the targeted reskilling occupation. Figure (a) shows respondents' self-reported share of skills in the treatment occupation. Figure (b) shows the share of skills in the treatment occupation that the person has according to O^*Net data. The proportion of skills acquired from previous occupations that are used in the treatment job, or the "share of skills", represents the extent to which an individual's existing skills align with the complete set of skills required for a specific treatment job. A 0% share indicates that none of the individual's past job skills are applicable to their new role, while a 100% share suggests full applicability of past skills to the treatment occupation. The calculation of the skills share is performed in two manners: one based on the participants' self-assessment in the survey and the other using the Lightcast indicator for the skill distance between the past job and the treatment occupation. In both methods, the share is the ratio between the respondent's number of skills and the total number of skills required to perform the treatment jobs.

Figure A13: Share of skills acquired from previous occupation used in the treatment job

(a) Share of skills possessed by individuals



(b) Proportion of individuals possessing each skill



Note: Figure (a) shows the proportion of skills acquired from the previous occupation that is used in the treatment job according to participants' perception and according to the ISCO classification of their past jobs; Figure (b) shows the percentage of individuals possessing a certain skill according to their perception and according to O^*Net classification of their past jobs.