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Empowering refugees: The role of comprehensive training programs in labor market integration

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Empowering refugees: The role of comprehensive training programs in labor market integration*

Chiara Zisler†, Eric Bettinger‡, Uschi Backes-Gellner§

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Abstract

Given the increase in global refugee and migration flows and the severe labor shortages in host countries, actively helping refugees enter the labor market constitutes a critical need. Targeted training programs for refugees can potentially improve labor market and social integration. Using a quasi-experimental approach, we investigate a comprehensive Swiss IT and coding bootcamp that combines occupational skills training with workplace-based cultural skills training (i.e., implicit skills that can be learned only through work experience). By matching individual survey data with detailed records from the program application process, we compare the labor market and social integration outcomes of program applicants around the admission threshold. We show that program participation significantly improves labor market outcomes compared to non-participation within the first three years after program graduation. Our results provide valuable insights for policymakers designing refugee integration policies, showing that training programs that complement high-demand technical skills with workplace-based cultural skills training effectively improve refugees' labor market outcomes. While previous research has largely examined broader, low-skilled training programs, we provide the first evidence on the effectiveness of specialized high-skill training programs for refugees. These programs not only help alleviate critical skill shortages but also facilitate refugees' broader economic and social integration into host countries.

JEL classification: J61, M53
Keywords: Refugees, Labor market integration, Skills training, Natural experiment

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1. Introduction

Global refugee and migration flows have been steadily rising due to a growth of armed conflicts, political persecution, and environmental disasters (Becker & Ferrara, 2019; UNHCR, 2022). The UN Refugee Agency's 2022 statistics on forced displacement show that the global refugee population increased substantially, from 27.1 million in 2021 to 35.3 million in 2022, marking the most significant annual surge on record (UNHCR, 2022). Yet, despite their oft-times high educational qualifications, refugees encounter challenges integrating into the labor market of their host country (Fasani et al., 2022; Ruiz & Vargas-Silva, 2018; Schuettler & Caron, 2020). For example, Müller et al. (2023), analyzing refugees' labor market integration in Switzerland, show that within the first one to two years after arrival, refugees experience 80 percentage points lower probabilities of employment than natives on average—and that, even after 19 to 20 years, a substantial disparity persists. At the same time, many host countries face severe labor and skills shortages in many sectors (e.g., IT) (Brunello & Wruuck, 2021; Cappelli, 2015; Mason, 2018). By integrating refugees better into the workforce, these countries could mitigate both their labor shortages and demographic challenges, reduce social welfare dependency, and enhance social integration of refugees.

For supporting refugees' labor market integration, two distinct types of skills may play important roles: occupational skills required in the host country and workplace-based cultural skills required in host country firms. First, given that refugees face forced and often unexpected migration, they can rarely choose their country of destination and may possess fewer occupational skills applicable to their host country than economic immigrants[1] have, leading to lower employability prospects (Brell et al., 2020; Demirci & Kirdar, 2023). In this context, targeted occupational skills training such as active labor market programs (ALMPs), could be helpful in increasing their labor market integration by aligning their skills with those most needed in the

[1] In this paper we distinguish between "refugees," i.e., individuals forced to flee conflict or persecution (UNHCR, 2023), and "economic immigrants," i.e., voluntary migrants according to the economics migration literature (e.g., Becker & Ferrara, 2019; Brell et al., 2020; Dustmann et al., 2017).

host country (Card et al., 2018; Katz et al., 2022). Yet, the extensive literature on ALMPs notwithstanding (Bredgaard, 2015; Katz et al., 2022; Kluve, 2010; Kluve et al., 2019) limited empirical evidence exists on the effects of such programs for refugees, except for studies on job search assistance and language courses for immigrants (Andersson Joona & Nekby, 2012; Battisti et al., 2019; Foged & van der Werf, 2023; Lochmann et al., 2019; Sarvimäki & Hämäläinen, 2016). Second, refugees may possess fewer workplace-based cultural skills (i.e., tacit, often unspoken norms and behaviors that are prevalent in the host country's labor market and can be acquired only through work experience) common to their host country than economic immigrants. For refugees, workplace-based cultural skills often represent an invisible barrier because they are unfamiliar with the labor market and institutions of the host country and thus often unaware of the implicit skills they may lack (Zorlu, 2016). Therefore, teaching these workplace-based cultural skills in addition to occupational skills may further improve refugees' prospects of labor market integration. While Zisler et al. (2023) show that workplace-based cultural skills are particularly helpful for integrating adolescents with migration backgrounds (i.e., economic immigrants and refugees) and high cultural and temporal distances from their host countries into the labor market, the role of these skills in integrating adult refugees remains unexamined. Since refugees often have less acculturational opportunities and higher language barriers than economic immigrants, we expect workplace-based cultural skills training to be even more essential for their integration (Brell et al., 2020).

This paper analyzes the impact of targeted training programs—which train adult refugees in occupational and workplace-based cultural skills—on both labor market and social integration. Specifically, we investigate the information technology (IT) and coding bootcamp offered by the Swiss non-profit organization (NPO) Powercoders. It offers a 13-week, intensive in-class training in both IT and coding skills, both of which are in high demand in the Swiss labor market. Powercoders also facilitate internships at IT firms. Moreover, program participants receive individual labor market and job coaching. Consequently, beyond learning typical

occupational IT and coding skills, participants also acquire workplace-based cultural skills. Given that the Powercoders program comprises these two important skill types, we expect an overall strong positive program effect, i.e., more beneficial labor market (and social integration) outcomes for training participants than for comparable rejected applicants around a budget-induced, quasi-random cutoff line. With additional survey data, we investigate the role of workplace-based cultural skills in this positive effect.

To compare labor market outcomes of program participants and for rejected, non-participating applicants, we conducted a comprehensive online survey with three cohorts of Powercoders applicants. In addition to collecting data on labor market outcomes (i.e., employment and the probability of working in an IT occupation), we also collected data on social integration outcomes (e.g., perceived integration and trust). Moreover, we surveyed proficiency in specific workplace-based cultural skills and collected a rich set of information on applicants' background characteristics. Powercoders then matched our survey data to their own detailed records from the application process, i.e., quantitative information on the applicants' performances on Powercoders assessment tests.

To identify the program effect, we proceed in two steps. First, we start with naïve ordinary least squares (OLS) regressions that compare all participants to all rejected applicants. However, these estimations partly reflect applicants' unobserved ability differences. To identify causal effects, we need a sample of applicants who are almost identical and differ only in their training participation. Therefore, second, we use applicants' performance scores and application outcomes to construct a quasi-experimental setup. Using the performance data from the application process, we identify all applicants close to the program admission cutoff across different cohorts. We then compare applicants who were just slightly above the admission threshold and admitted to the program, with those who were slightly below the threshold and thus very similar but not accepted because of lack of space. By doing so, we create a setup that

approximates random assignment and thus allows causal estimations of the program's effect on refugees' labor market and social integration.

The results of a first naïve regression comparing all participants to all rejected applicants show a 51 percentage points higher employment probability for participants. In our subsample of quasi-random participants and non-participants, we find a 42 percentage points higher employment probability—a large and substantial effect given the mean employment rate of 26% in the control group. While it may be tempting to compare this effect to ALMPs for natives, it is essential to contextualize it within the refugee employment situation in Switzerland. The most relevant comparison for the Swiss context comes from Müller et al. (2023), documenting that the employment gap between refugees and natives narrows most sharply in the initial years following arrival. In our study, refugees have been in Switzerland for an average of three years. Given that Müller et al. (2023) show that between years three and nine post-arrival, the employment gap decreases by 44 percentage points, from 72 to 28 percentage points, the 42 percentage point increase in refugees' employment probability corresponds to speeding up the integration process by about 5.7 years (see Fig. A1). In other words, the Powercoders program helps refugees catch up to the labor market outcomes of their native counterparts much faster, as if they had already spent more time in their host country, thereby accelerating the closure of native-refugee employment gaps.

When exploiting our rich survey data to understand underlying mechanisms, we find suggestive evidence that increased workplace-based cultural skills may be at the heart of the observed differences in the employment probability. In additional analyses, we studied not only the probability of employment but also the quality. Specifically, we examined whether refugees found employment in their trained field, i.e., IT, rather than simply taking any jobs that do not match their qualifications. Finally, we examined whether program participants subjectively feel better socially integrated. We find positive results for all these additional outcomes.

Our paper makes two important contributions to the economics literature. First, it contributes to the strand of migration literature that has already identified important factors possibly affecting refugees' labor market integration, such as their legal status (Devillanova et al., 2018), the length of the asylum process (Hainmueller et al., 2016), or the imposition of employment bans (Fasani et al., 2021). We add the role of different types of skills training for refugees as another important factor. Specifically, we analyze whether teaching occupational and workplace-based cultural skills can help refugees integrate into the labor market. Second, our paper contributes to the ALMP literature that has thus far analyzed job search assistance programs and language training for immigrants and refugees (Foged et al., 2024b; Foged & van der Werf, 2023; Lochmann et al., 2019). We add to this literature by examining both the labor market effects and the social integration effects of comprehensive training programs that teach both occupational skills and workplace-based cultural skills. Moreover, we are the first to measure explicitly refugees' self-assessments in six dimensions of workplace-based cultural skills and show that these skills may constitute a mechanism for better labor market integration.

The rest of the paper is structured as follows. Section 2 provides background on the Powercoders program. Section 3 describes the data, Section 4 explains the empirical strategy, and Section 5 presents the results and discusses the implications. Section 6 concludes.

2. Background on Powercoders program

We study the IT and coding skills training program provided by Powercoders, a Swiss NPO specializing in training refugees. Powercoders' main aim is to help refugees enter the IT sector, secure permanent employment, and become financially independent in the Swiss labor market. Receiving financial support from private firms, foundations, and the Swiss government, e.g., the State Secretariat for Migration (SEM), Powercoders offers its programs to selected participants free of charge. They started what they call their "Coding and IT Bootcamp" in

Switzerland in 2017 (Powercoders, 2023). The bootcamp program that we analyze targets refugees in Switzerland aged 18-55. Given that refugees have a more difficult time integrating into the Swiss labor market than economic immigrants, most program openings are reserved for those with official refugee status. Eligible participants must reside in Switzerland and possess the legal right to work (i.e., holding permit F, S, B, or N in Switzerland).[2] Because few refugees speak any of the four Swiss national languages (French, Italian, German, or Romansh), the program is conducted in English, a language commonly used in Swiss businesses. While applicants must therefore demonstrate sufficient English language proficiency, they do not require a specific English certificate.

The program curriculum in 2021-2023 (the period we studied) focused on two types of skills. First, it included occupational skills training for IT professions (e.g., coding skills), with all participants attending a 13-week intensive full-time programming course, with specialized tracks in web design, Java, advanced Java Script, testing, and DevOps (i.e., an approach that combines software development (Dev) and IT operations (Ops) and aims at an efficient and reliable software delivery).

Second, the program trained workplace-based cultural skills, including understanding the Swiss labor market and its workplace norms, social behavior, and business customs. Participants learn and practice these skills in weekly in-person training sessions, including role playing, all of which form the foundational layer for learning workplace-based cultural skills in the workplace. Another essential condition for fully acquiring such skills is practical in-firm training in real-life work settings. Participants attend Powercoders "career days" after program completion, receiving the opportunity to conduct speed interviews with different firms and secure

[2] In Switzerland, permit F in Switzerland, for "provisionally admitted foreigners," allows certain foreign nationals to stay for reasons of unlawful, unreasonable, or impossible expulsion. Initially valid for twelve months, it is extendable and permits employment in Switzerland. Permit S for "people in need of protection," offers a provisional stay without residency rights. Employment and job changes require permission, and permit holders must present the permit to potential employers. Permit B is for "recognized refugees" who have been granted asylum. Recognized refugees are permitted to work anywhere in Switzerland. While permit B is limited to one year, it is usually extended as long as the reasons for refugee recognition persist. Permit N for "asylum-seekers" with pending asylum applications, allows them to pursue gainful employment under certain circumstances (SEM, 2023).

an internship for 6-12 months. Throughout those internships, participants receive individualized support from a job coach and financial support, if necessary, for laptops, food, and transportation.

Powercoders opens its program application periods twice a year, in spring and fall, attracting 200-300 applicants per period. The selection process comprises three stages: First, applicants submit their applications online via the Powercoders website. Powercoders then screens and rates them with a point system.[3] Depending on the grading, it invites a selected group to a second round, to work on specific take-home assignments and take several IT tests, which Powercoders again rates on a point system. This second phase also evaluates their ability to meet deadlines and work independently on tasks. From all these second-round applicants, Powercoder's recruiting team selects about 50 applicants for a third round and invites them to a personal interview, which it again rates on a point system. Budgetary restrictions limit Powercoders to accepting only the 30 best of these interviewees to participate in the program; the other approximately 20 receive a rejection after this third round. Overall, Powercoders uses a clearly structured evaluation scheme to assess applicants in their three-stage process. At each stage the evaluation is based on a point system ensuring a consistent and objective selection process across different raters. At each stage, the raters convene to systematically assess applicants' performances and collectively determine advancement decisions.

[3] Applicants received a grade on a scale from 100 to 400. A score of up to 100 reflects a performance below expectations; up to 200, an average performance with significant potential for improvement; up to 300, a good performance; and up to 400, an outstanding performance. In instances when applicants either did not submit their assignments or failed to progress to the next stage of the application process, Powercoders assigned them a score of zero to reflect their non-participation or lack of progress.

3. Data and operationalization

Datasets and matching

For our empirical analyses, we combine two data sources. First, we rely on Powercoders' data on applicants' performance records from the application process. This dataset provides us with the main explanatory variable, a binary variable for program participation (i.e., accepted into the program/not accepted into the program). Moreover, the quantitative performance ratings allow us to identify comparable applicants, those point ratings were very close, but with some just above and some just below the admission threshold. The data also includes a variable for the cohort in which the applicants applied, a variable that we use as a control.

Second, we use survey data. Powercoders matched the performance data to data from an online survey that we ran in November 2023 to collect data on respondents' labor market situation, their workplace-based cultural skill levels, their social integration, and essential control variables. This last group includes demographic characteristics such as age, gender, canton of residence,[4] nationality, country of origin, type of permit, year of arrival in Switzerland, educational background, prior IT working experience, or participation in other IT programs. For privacy reasons, Powercoders conducted the matching of the two datasets.

To design and test our survey questionnaire, we conducted qualitative pilot interviews with alumni of the Powercoders program and engaged in discussions with Powercoders recruiters. These interviews allowed us to design the questionnaire in a way that anticipated the specific challenges refugees might face when responding to the survey. Moreover, with these interviews and consultations with Powercoders, we were able to identify six key dimensions of workplace-based cultural skills with which refugees typically struggle and integrate them into the survey. Finally, the interviews helped us to determine the appropriate questions for measuring social integration in our special group of survey participants.

[4] Cantons are distinct administrative entities in Switzerland much like states in the US.

Questionnaire design and operationalization of outcome variables

Drawing on the economics literature, insights from pilot interviews, and discussions with Powercoders and its alumni, we derived three types of outcome variables. First, we examine two labor market outcomes. The main variable of interest is whether an individual is in "employment" or not. It is a binary variable: employed versus not employed, measured at the time of the survey. As second labor market outcome, because the program's aim was to help refugees obtain IT jobs, we use "employment in an IT job" as a qualitative employment dimension. It is also a binary variable: being employed in an IT occupation or not.

Second, to analyze whether workplace-based cultural skills may be an important mechanism for better employment outcomes, we use these skills as outcome variables. Specifically, we investigate six skill dimensions: (1) "understanding Swiss business customs," (2) "resolving conflicts," (3) "understanding punctuality and deadline rules," (4) "understanding hierarchies and authorities," (5) "understanding and adhering comfortably to ethical principles," (6) "navigating social interactions comfortably." We rate each dimension on a 5-point Likert scale, with 5 the highest and 1 the lowest skill level. For a more intuitive interpretation of the skill effect sizes in our empirical analyses, we transformed these ratings to standard deviation (SD) units.

Third, we examine three social integration outcomes. Following Harder et al. (2018), we use "perceived social integration in the host country" and the "perception of living in a supportive environment" as outcome variables. We asked respondents to rate on a 5-point Likert scale "How much do you feel integrated in Switzerland?" and how much they agree with the statement "I am currently living in a supportive social environment". Moreover, given that refugees often suffer from severely compromised trust levels due to exposure to armed conflicts, trauma, or uncertainty in the host country, in turn impairing their economic and social integration, trust levels—which measure an individual's trust in society in general and in government institutions in particular—are critical to our study design (Demirci & Kirdar, 2023;

Essex et al., 2022; Hainmueller et al., 2016).[5] Thus, in line with Butler et al. (2016), our survey measures trust levels by asking respondents the question "Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?" Again, for intuitive interpretations, we transformed the scale ratings of all these social outcomes into SD units.

Sample

In November 2023, we sent the final questionnaire to all Powercoders applicants who applied to the program in 2021, 2022, and 2023. To ensure a sufficient number of responses from both accepted and rejected applicants, we incentivized the survey by offering each respondent (whether accepted and rejected) a voucher of 10 Swiss Francs for a coffee or a small breakfast.[6] We sent the questionnaire to 1,343 applicants and reached a very good response rate of 30.6%.[7] Among program participants the response rate was 51.4%; among rejected program applicants, as expected, the response was a bit lower but still at a very good rate of 27.33%.[8] Given that response rates in online surveys typically range between 5% and 30% and the challenge in surveying refugee populations is particularly high, both response rates are very satisfying (Wenzel et al., 2022). However, as the difference in response rates between program participants and rejected applicants may raise concerns about potential selection bias, we address this issue in section 6. To ensure that our findings are not driven by selection bias, we apply a

[5] Alesina and LaFerrara (2002) show that factors such as having a recent history of traumatic experiences, belonging to discriminated groups, facing economic disadvantage in terms of income and education, and residing in economically disparate communities are strongly linked to lower levels of trust. These factors apply to many refugees. However, Oreopoulos and Salvanes (2011) find that education can help improve trust levels, in turn improving social integration and community involvement.

[6] Overall, the take-up rate for the vouchers was 63.5%. Among participants, the take-up rate was 69.1%; among non-participants 61.8%.

[7] Of the 1,343 Powercoders applicants we contacted, 411 participated in the survey. They come from a large number of countries, with Turkey, Ukraine, Afghanistan, and Ethiopia being the most prominent (see Fig. A.2 in the appendix).

[8] Of 1,160 rejected applicants, 317 responded (27.3% response rate). Of 183 former program participants, 94 responded (51.4% response rate).

Lee bounding approach (Lee, 2009), which accounts for differential response rates between the two groups. Lee bounds allow us to estimate a range within which the true treatment effect lies, even under extreme assumptions about non-respondents' employment outcomes. We discuss the results of this robustness check in Section 6 and conclude that selection bias is unlikely to drive our results.

The survey slightly suffers from late-stage survey dropouts, with 32% of respondents not completing the entire questionnaire, i.e., for 130 individuals we do not have a full set of variables, particularly some additional demographic questions asked at the end of the survey. We discuss and deal with the consequences of missing variables in the empirical analyses in Section 4.

Descriptive statistics

Table 1 presents the summary statistics of survey respondents who participated in the program (treatment group) and rejected applicants (control group). These descriptive statistics show that across all essential background characteristics, applicants in both groups are highly similar. These characteristics include age, gender, participation in other IT programs, prior IT work experience, and educational background in terms of highest degree obtained and the educational field. T-tests confirm that no significant differences exist between the two groups for any of our background variables, thereby supporting our assumption that applicants in the treatment and control groups are sufficiently balanced.

In addition to showing that treatment and control groups are similar in observable background characteristics, Table 1 also reports substantial differences in their labor market outcomes. The 79% employment rate in the treatment group is substantially higher than the 26% in the control group. Moreover, as Table 1 shows this difference does not come at the cost of lower employment quality: the 92% probability of working in an IT occupation in the treatment

group is much larger than the 34% in the control group. The t-tests show that the differences are significant at the 1% level.

Table 1
Summary statistics of treatment and control group

	Treatment Group (Participants)	Control Group (Non-Participants)	Treatment Difference	
	Mean	Mean	(T-statistic)	*N*
Background characteristics				
Age	37.833 (7.439)	38.456 (8.395)	0.622 (0.57)	268
Male	0.739 (0.443)	0.610 (0.489)	-0.123 (-1.81)	268
Alternative IT program	0.455 (0.502)	0.436 (0.497)	-0.019 (-0.27)	268
IT work experience (binary)	0.348 (0.480)	0.322 (0.468)	-0.027 (-0.40)	268
IT work experience (in years)	2.129 (4.464)	1.938 (4.238)	-0.191 (-0.31)	268
Upper secondary degree	0.015 (0.123)	0.025 (0.155)	0.010 (0.46)	268
Bachelor's degree	0.500 (0.504)	0.550 (0.499)	0.050 (0.70)	268
Master's degree	0.303 (0.463)	0.292 (0.456)	(-0.011) (-0.17)	268
Education 'IT'	0.197 (0.401)	0.218 (0.414)	0.021 (0.36)	268
Education 'Business, Administration, and Law'	0.197 (0.401)	0.178 (0.384)	-0.019 (-0.34)	268
Education 'Engineering'	0.197 (0.401)	0.154 (0.361)	-0.044 (-0.83)	268
Labor market outcomes				
Employed (binary)	0.788 (0.412)	0.262 (0.441)	-0.526*** (-8.54)	268
Probability of working in an IT occupation (binary)	0.923 (0.269)	0.34 (0.478)	-0.583*** (-7.69)	105

Notes: This table covers respondents from a Fall 2023 survey of individuals who applied to the Powercoders coding and IT bootcamp in 2021, 2022, and 2023. The data reflects only the subset of applicants who responded to the survey. Column 3 shows the t-test results, with t statistics shown in parentheses. Additionally, to account for potential correlations between the error terms of the separate regressions for the background characteristics, we conducted seemingly unrelated regressions (SUREGs). The SUREGs yield no significant differences in the background characteristics between the treatment and control groups, thereby confirming balance (the chi-squared statistic is 7.59 with a p-value of 0.474).
* p<0.05, ** p<0.01, *** p<0.001

Aiming at causal estimations, we refine our analysis by using two samples (close to the admission threshold) that result in more homogeneous applicants. The summary statistics for the treatment and control groups for these refined samples appear in Tables A.1 and A.2 in the

appendix. These statistics again confirm that respondents in both groups are very similar across essential background characteristics, and the t-tests yield no significant differences.

4. Empirical strategy

In our empirical strategy, we proceed in two steps, which both use the same OLS estimations equation:

$$y_i = \beta_0 + \beta_1 T_i + \beta_2 X_i + u_i \qquad (1)$$

where y_i denotes the outcome; T_i is a binary variable that indicates the treatment status (i.e., participation or non-participation in the Powercoders IT and coding bootcamp) of individual *i;* and X_i is a vector of individual control variables.

In a first step, we start with naïve OLS regressions, in which we use all applicants, i.e., we compare all program participants to all rejected applicants in our sample. In a second step, to eliminate ability differences and estimate causal effects, we use the quasi-randomness of the cutoff line, separating applicants with only minor and imprecise differences in their application scores. Fig. 1 illustrates the sample restrictions that we use in these two steps. The naïve OLS regressions use the full sample of 411 observations. In this sample, the control group was much larger and more heterogeneous than the treatment group, with 317 and 94 observations, respectively. To focus on applicants of similar abilities, we narrow down our sample to all applicants who successfully passed Powercoders' first two selection rounds and reached the final interview stage (refined sample 1). We then again narrow down our sample and keep only respondents whose performance scores were very close to the program admission threshold on either side of the cutoff. Specifically, we include the group of applicants right above the threshold which consists of 19 individuals and the same number of 19 applicants just below the threshold. In doing so, we exclude the very high-performing interview applicants from the treatment group

and the very low-performing applicants from the control group.[9] In this most-refined sample we have 38 observations split evenly between the treatment and control groups (refined sample 2).

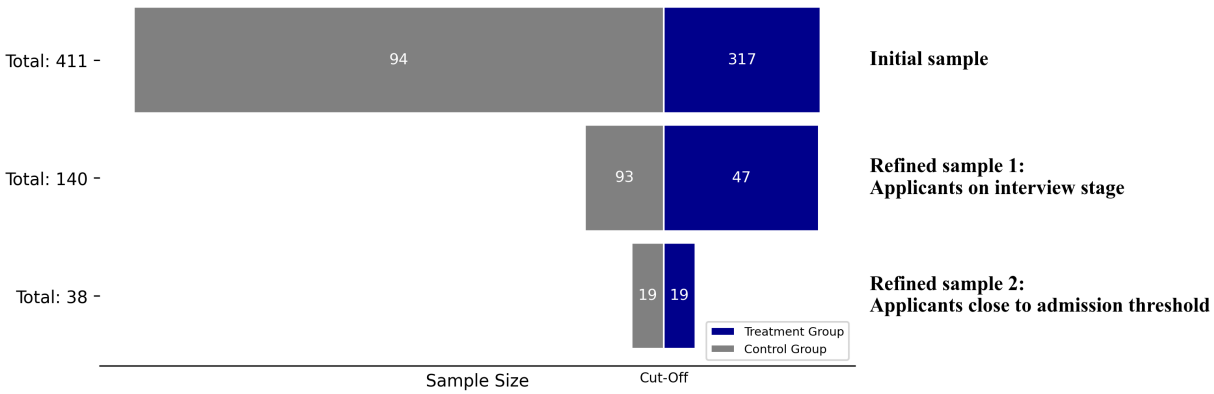

Fig. 1 Sample restriction – Building homogeneous samples.

We argue that one can interpret the estimations with refined sample 2 as causal, conditional on two assumptions. First, this heavily refined sample comprises homogeneous applicants who (a) have already successfully passed two selection stages and reached the final interview stage, and (b) performed just slightly above or below a budget-induced admission threshold. Second, the nature of qualitative interviews inherently involves some degree of imprecision. The evaluation of applicants in such interviews is imprecise in that those who perform barely above or barely below the threshold are no longer meaningfully distinguishable. Thus while applicants around the cutoff may have marginally different scores, their underlying abilities remain comparably high, reflecting the subjective nature of scoring. Moreover, as Powercoders has a constant capacity restriction of 30 program openings, the admission

[9] To construct the most refined sample (refined sample 2), we examined the score distribution in Table A.8 and identified the narrowest possible range around the admission cutoff that maximized applicant similarity while maintaining a balanced number of observations in the treatment and control groups. Table A.8 in the Appendix presents the full distribution of the interview rating scores.

threshold is independent of the number of applications.[10] Consequently, we argue that the applicants in refined sample 2 have very similar abilities and differ only in whether or not they participated in the training.

5. Results

Labor Market Outcomes

Table 2 presents our naïve regression estimations of program participation on our main outcome, the employment probability. It comprises three models, all showing a positive association between participation in the Powercoders program and employment probability. In Model I, which does not include any control variables, we observe that program participation relates to a 51 percentage points increase in employment probability compared to non- participation. After adding control variables in Model II, we observe an even higher association, with a coefficient of 68 percentage points. However, in this model, we face a severe loss of observations (N=268 instead of 406). Because we asked for most control variables at the end of the online survey, and not all respondents completed the full questionnaire, we lose several observations when we include all control variables. To mitigate this loss, in Model III, we integrate a regression with missing imputations.[11] This model shows that program participation correlates with a 47 percentage points increase in employment probability. While this effect size is relatively large, we discuss and demonstrate in Section 6 that it is realistic.

[10] A common concern in quasi-experimental designs is non-compliance, where admitted applicants do not enroll or do not complete the program. However, in our setting, non-compliance is negligible. Over the past 3.5 years, only 3% of accepted applicants either declined to start or withdrew, primarily due to job offers or health-related reasons. Given this low dropout rate, systematic non-compliance is unlikely to introduce bias in our treatment effect estimates.

[11] To ensure the inclusion of all cases, imputation methods aim at replacing missing values with plausible estimates (Little and Rubin, 1989). We use mean imputations, a common imputation approach (Little and Rubin, 1989). Specifically, for the control variables with missing values—i.e., nationality, participation in other IT programs, canton of residence, time in Switzerland, gender, educational background (field, highest degree obtained)—we replace the missing values with the sample mean of the respective variable.

Table 2
Employment probability – Naïve OLS regressions with all applicants

Dep var.	I Employed	II Employed	III Employed
Bootcamp participation	0.505***	0.681***	0.474***
	(0.053)	(0.086)	(0.057)
Controls	No	Yes	Yes
R-square	0.185	0.531	0.212
Observations	406	268	406

Standard errors in parentheses. OLS regressions. The dependent variable is employed as a binary variable. Independent variable is coding bootcamp participation. Controls: age, gender, nationality, participation in other IT program, prior IT work experience, canton of residence, educational background (field, highest degree obtained), time in Switzerland, cohort. Model I: OLS without controls. Model II: OLS with all controls. Model III: OLS with missing imputations and all controls.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Even though these naïve regressions yield insightful descriptive results, we are aware that unobserved ability biases these estimations. To eliminate these biases, we therefore estimate our refined sample regressions with more homogeneous applicants and show the results in Table 3.

In Models I and II of Table 3, we analyze refined Sample 1, which comprises all applicants who reached the final interview stage. While Model I is without controls, Model II includes three important control variables. The first two variables, controlling for ability differences that the final scores at the third stage may not capture, are the applicants' scores at the first and the second stage of the application process. The third control variable, controlling for time-varying external factors such as labor market tightness or economic up- or downswings, is the application cohort. Again, both models demonstrate a positive and highly significant association between program participation and the refugees' employment probability. Specifically, Model I shows a 54 percentage points increase in employment probability for participants compared to rejected applicants. In Model II, when we additionally control for applicants' first and second stages scores and the cohort, we obtain a similar coefficient.

Table 3
Employment probability - Refined sample regressions

	Refined sample 1 (Interview stage)		Refined sample 2	
	I	II	III	IV
Dep var.	Employed	Employed	Employed	Employed
Bootcamp participation	0.539***	0.530***	0.468***	0.422**
	(0.071)	(0.080)	(0.162)	(0.204)
Controls	No	Yes (Scores stage 1&2, cohort)	No	Yes (Scores stage 1&2, cohort)
R-square	0.295	0.305	0.189	0.255
Observations	140	140	38	38

Standard errors in parentheses. OLS regression.
The dependent variable is employed as a binary variable. Independent variable is coding bootcamp participation.
Models I and II comprise all applicants who reached application stage 3, i.e., those who had an interview with Powercoders.
Models III and IV include applicants who reached stage 3 and who received scores close to the admission threshold.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Models III and IV of Table 3, we use refined sample 2, which comprises all applicants who performed close to the admission threshold on the final interview stage. Excluding high-performers in the treatment group and low-performers in the control group, we obtain the most homogeneous sample with refined sample 2. In Model III, without controls, we find that the treatment group experiences a 47 percentage points higher employment probability than the control group. This effect is significant at the 1% level. Given that the average employment rate in the control group is 26%, the combined training in IT skills and workplace-based cultural skills in the Powercoders program is expected to result in 73% of participants securing employment. In Model IV, which again controls for the cohort and the scores achieved at the first two stages of the application process, we find that the treatment group has a 42 percentage points higher employment probability than the control group. As a robustness check, we include applicants' interview scores as controls in Models I and II of Table A.5, and the effects are consistent with the main analysis. In sum, after progressively approaching our quasi-experimental setting, we still observe a substantial program effect on refugees' employment prospects. We conclude that the program has a very large and economically highly significant effect on refugee

employment. Drawing on related ALMP studies, Section 6 discusses and provides evidence on the plausibility of this observed effect size.

One main aim of the Powercoders program is the permanent placement of trained refugees in the IT sector. Therefore, as a second labor market measure, we examine the probability of being employed in an IT occupation (Table 4). This measure indicates employment quality. In all three models in Table 4, we compare only employed applicants, i.e., employed program participants and employed non-participants. In Model I, including all essential control variables, we use the initial sample (i.e., all applicants) with 105 observations. The results show that program participation correlates with a 46 percentage points higher employment probability in an IT occupation. In Model II, we use refined sample 1, with 74 observations. As this sample is already very small and contains only very homogeneous applicants, we avoid further reduction of the sample by adding only control variables for the application cohort and the scores at the first and second stages. Again, we find that participation is associated with a much higher probability of employment in IT at 56 percentage points. In Model III, we use refined sample 2, with only 13 observations remaining. The estimation shows that program participants experience a very large increase (83 percentage points) in the probability of being employed in an IT job when compared to non-participants. However, as the estimation uses very few observations, this final effect requires careful interpretation.

Table 4
Probability of working in IT occupation

	Initial sample	Refined sample 1 (Interview stage)	Refined sample 2
	I	II	III
Dep var.	Employed in IT	Employed in IT	Employed in IT
Bootcamp participation	0.458**	0.564***	0.833***
	(0.174)	(0.127)	(0.153)
Controls	Yes (all)	Yes (Scores stage 1&2, cohort)	No
R-square	0.750	0.255	0.729
Observations	105	74	13

Standard errors in parentheses; The dependent variable is the probability of being employed in an IT-related job. Independent Variable: coding bootcamp participation. Controls: cohort, the scores on application stage 1 and 2. Model I uses the initial sample with all applicants. Models II comprises all applicants who reached application stage 3, i.e., those who had an interview with Powercoders. Models III includes applicants who reached stage 3 and who received scores close to the admission threshold. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Workplace-based cultural skills

We now test our hypothesis that the combined acquisition of workplace-based cultural skills and specific occupational skills (IT skills) constitute one essential mechanism for refugee labor market integration. Although we cannot fully disentangle the effect of IT skills and workplace-based cultural skills, we can nevertheless test whether participants exhibit higher levels of specific workplace-based cultural skills than non-participants. Instead of including these skills as control variables (as in Table 3), we follow Lochmann et al. (2019), by using them as potential outcome variables.[12] Table A.3 in the appendix reports the correlations between program participation and the six workplace-based cultural skill dimensions. These dimensions are (1) "understanding Swiss business customs," (2) "resolving conflicts," (3) "understanding punctuality and deadline rules," (4) "understanding hierarchies and authorities," (5) "understanding and adhering comfortably to ethical principles," and (6) "navigating social interactions comfortably."

[12] In doing so, we circumvent the "bad control" problem that causes selection bias (Angrist and Pischke, 2009).

The results in Table A.3 show that bootcamp participation strongly correlates with an increase in almost every workplace-based cultural skill dimension.[13] We observe the strongest increase at 0.5 SD in "understanding punctuality and deadline rules." Moreover, we identify strong increases at 0.3 SD in "understanding hierarchies and authorities," "understanding Swiss business customs," and "understanding how to solve conflicts." We observe a small but significant increase at 0.2 SD in "navigating social interactions comfortably." In contrast, we find no substantial increase in "understanding and adhering comfortably to ethical principles." Overall, these findings provide strong supportive evidence for our expectation that training workplace-based cultural skills (in combination with occupational IT skills) is an important driver for the observed changes in labor market outcomes. In Table A.4, we add essential control variables and demonstrate that the results remain robust across these specifications. However, the coefficient for "navigating social interactions comfortably" becomes insignificant.

Social integration outcomes

Table 5 shows results for our three social integrations outcomes: (1) perception of living in a supportive environment, (2) perception of host country integration, and (3) general trust in society. Estimations with the full sample in Models I, II, and III[14] show that bootcamp participation strongly correlates with an increase in the perception of living in a supportive social environment (0.6 SD), the perception of host country integration (0.4 SD), and trust (0.4 SD).

Estimations with refined sample 1 in Models IV, V, and VI show again that bootcamp participation is strongly correlated with social integration. In these models, we observe even stronger associations—with coefficients of 0.7 SD—between program participation and both

[13] Although we use the initial sample for these estimations, attrition in the survey questionnaire leads to only 295 observations in this model, because workplace-based cultural skills are not full reported by all respondents. All coefficients show the difference in the reported skill levels in SD units.

[14] As we use the full sample in these models, we use all control variables to reduce heterogeneity across individuals.

the perception of living in a supportive social environment and host country integration. However, the coefficient for our trust measure, while still positive, becomes insignificant.

Table 5
Program participation and social integration outcomes

	Initial sample			Refined sample 1 (Interview stage)		
	I	II	III	IV	V	VI
Dep var	Supportive social environment	Perceived integration level in host country	Trust	Supportive social environment	Perceived integration level in host country	Trust
Bootcamp participation	0.622*** (0.162)	0.425*** (0.158)	0.398** (0.170)	0.727*** (0.180)	0.676*** (0.181)	0.167 (0.217)
Controls	Yes (all)	Yes (all)	Yes (all)	Yes (scores stage 1&2, cohort)	Yes (scores stage 1&2, cohort)	Yes (scores stage 1&2, cohort)
R-square	0.340	0.388	0.305	0.162	0.174	0.052
Observations	284	284	284	109	109	109

Standard errors in parentheses.
Model I and IV: The dependent variable is living in a supportive social environment in SD units. Model II and V: The dependent variable is perceived integration in SD units. Model III and VI: The dependent variable is trust in SD units. Independent variables coding bootcamp participation. Model I to III include the following controls: age, gender, nationality, educational background (field), highest degree obtained, cohort, time in Switzerland.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6. Discussion and Conclusion

We shed light on the role of training programs that contain two types of skills—IT skills combined with workplace-based cultural skills—for refugees' economic and social integration. Our study breaks new ground in at least two ways. First, we are the first to analyze the potential value of training programs combining these two skill types for refugees' labor market integration. We examine whether workplace-based cultural skills acquisition is an important mechanism that could partly explain the improved labor market prospects of program participants compared to rejected applicants. In so doing, we look at essential albeit often neglected skill types such as understanding the host country's business customs. Second, to estimate the causal

effects of such training programs on labor market integration, we are able to exploit a natural experiment setting.

We argue and present evidence that participating in targeted training programs that comprise IT skills and tacit workplace-based cultural skills significantly and very strongly increases refugees' labor market outcomes. Specifically, we find that such programs increase refugees' employment probability by 42 percentage points. Thus, the program expedites refugees' employment progress as if they had already resided in their host country for an additional 5.7 years. One potential concern is that this large effect may be overstated due to different response rates between the treatment and control groups, with the treatment group showing a 24 percentage point higher response rate. For example, if all non-respondents in the control group (up to the point where response rates are equal) were employed, our estimate would be upward biased.

To deal with this concern, we apply Lee Bounds (Lee, 2009), which provide upper and lower bounds for the treatment effect under different assumptions about non-respondents' employment outcomes. First, we examine the worst-case scenario for estimating the program's effect, in which we assume that all non-respondents in the control group would have had the best possible employment outcome. Following this assumption, we artificially inflate the observed employment rate in the control group, resulting in a downward-biased estimate of the program's effect. We implement this adjustment separately for each sample. In the full sample, we randomly reassign 76 subjects from the control group (24% of 317 respondents) as employed. In refined sample 1, we reassign 11 subjects (24% of 47 respondents), and in refined sample 2, we reassign 5 subjects (24% of 19 respondents).

The results, presented in Table A.6, show that even under this conservative assumption, bootcamp participation increases employment significantly, with estimated effects ranging from 35 to 41 percentage points across different specifications. While the magnitude of the effect decreases relative to the baseline estimate, it remains statistically significant, thereby confirming that the program's impact is not solely driven by response bias. Even when applying

the strictest correction for non-respondents' employment status and using our most homogeneous sample—refined sample 2—program participation still increases employment probability by 39 percentage points.

Second, we examine the best-case scenario for estimating the program's impact, in which we assume that all non-respondents in the control group would have had the worst possible employment outcome (i.e., they would have been unemployed). Under this assumption, we artificially lower the observed employment rate in the control group, which in turn results in a larger estimated effect of bootcamp participation. Again, we apply this adjustment separately for each sample, randomly reassigning the same number of subjects as in the worst-case scenario but setting their employment status to unemployed. The results, presented in Table A.7, show a strong and significant positive effect of bootcamp participation on employment, with estimates ranging from 56 to 72 percentage points. Thus under the most favorable assumption, where non-respondents in the control group are assigned the lowest possible employment outcome, the estimated treatment effect is substantial but likely overestimated. However, the results in Table A.6 and A.7 clearly reinforce the conclusion that Powercoders strongly improves employment probability. Overall, the Lee Bounds estimates demonstrate that the effect is not solely driven by selective survey participation.

However, the effect size exceeds that reported in comparable studies examining refugee labor market integration. For example, our detected program effect is significantly larger than that of Battisti et al. (2019), who find a roughly 20 percentage points higher employment probability for officially unrecognized refugees,[15] participating in a job search assistance program. Their effect, while also relatively large, is smaller than ours. Yet, unlike the program in Battisti et al. (2019), which focused solely on job search assistance, the Powercoders program offers a more comprehensive training package, including high-demand IT skills training, workplace-

[15] Unrecognized refugees are individuals who have not yet been granted official refugee status.

based cultural skills training, individual job coaching, social networking opportunities, and a micro-credential upon program completion. In particular, the strong signaling effect of the micro-credential may further enhance the value of the acquired skills. This credential and the broader skill spectrum that Powercoders covers likely explains the much greater effect size that we observe. Overall, the large effect size in our study likely results from the combination of multiple training components and individualized support. This finding is consistent with Kluve et al. (2019), pointing out that employment programs integrating multiple services tailored to individual needs tend to be more effective than single-component programs.

Further studies that investigate single-component ALMPs are for example Foged et al. (2024a) or Andersson Joona and Nekby (2012). Using a regression discontinuity design, Foged et al. (2024a) evaluate a Danish reform that expanded mandatory language training for refugees. They find that enhanced language training led to a 9 percentage point increase in the probability of being employed in a job with high language and communication requirements. Andersson Joona and Nekby (2012) analyze intensified coaching by caseworkers in the Swedish Public Employment Services on immigrants' employment prospects. They observe that the coaching program raised men's employment probability by only 6 percentage points and find no significant effect for women.

However, since neither the language training nor the coaching program did include professional skills training, the greater effect of the Powercoders program, offering a broad range of training inputs, is plausible. Both studies also suggests that the large effect of Powercoders may stem from strong complementarities between different program elements, i.e., the combination of highly demanded occupational skills, labor market coaching, and workplace-based cultural skills. Another reason for the smaller effect sizes reported in the Andersson Joona and Nekby (2012) study compared to our results could be their focus on economic immigrants rather than refugees. Economic immigrants typically possess skills that align more closely with the host country's needs and therefore face fewer employment challenges than refugees.

Finally, studies focusing on multi-component ALMPs contribute to the understanding of our large effect sizes. The closest evidence to our own are Dahlberg et al. (2020), Arendt (2022), and Foged et al. (2024b), three exceptions in also analyzing refugee programs with multiple components. Yet, there is one key distinction between the Powercoders program and their programs of interest: they concentrate on refugees in low-skilled work rather than highly demanded IT and coding skills. Dahlberg et al. (2020) examine a Swedish program, including language training, job search assistance, and work practice. They report a substantial increase of 15 percentage points in the employment probability for participating refugees. However, their program strictly targets low-educated refugees and is limited to low-skilled work, potentially explaining the smaller effect size compared to our study.[16] Similarly, Arendt (2022) evaluates a Danish ALMP policy obligating refugees to engage in training components akin to those in the Swedish program. While he finds an increase of 10 percentage points in men's employment rates within a year, this policy also led to employment in precarious, low-hour jobs. The policy's focus on immediate job placement and its broader, less individualized training approach likely explains why the Powercoders bootcamp effect is larger. Foged et al. (2024b) reanalyze several Danish refugee policies, including the Industry Packages ALMP, which matched refugees to unfilled, low-wage manual jobs. They find an increase of 5.4 percentage points in employment probability.

We extend our analysis to a broader set of outcomes. We find that dual programs for refugees not only increase the employment probability but also the quality of that employment: refugees in these training programs also have a much higher probability of working in IT jobs. Moreover, in showing that program participants have substantially higher levels of workplace-based cultural skills than comparable but rejected applicants, we provide suggestive evidence that these skills play an important role in labor market integration, particularly when combined

[16] Participants in the Swedish program could choose between three job tracks: (1) indoor cleaning, (2) outdoor work (e.g., snow shoveling or maintenance), and (3) real estate caretaking (Dahlberg et al., 2022).

with occupational skills that are in high demand in the host country. We also demonstrate that the program participation significantly improves refugees' social integration and feelings of trust.

While acknowledging that external validity remains a challenge in research settings such as ours, we argue that our insights on the importance of dual type skills training for refugees are transferable to other countries as long as these programs (a) focus on occupational skills in high demand and (b) include a sufficient amount of practical components to enable participants to acquire essential workplace-based cultural skills. Indeed, having started its coding and IT bootcamp in Switzerland in 2017, Powercoders has already successfully replicated its program in Italy in 2019 and Spain in 2021 (Powercoders 2023).

We add two primary caveats two our study. First, the high qualification levels of the refugees in our sample (most hold a bachelor's or master's degree) may restrict the generalizability of our results, particularly of our estimated effect size, to refugees with different qualification levels. However, Zisler et al. (2023) find a strong positive effect of combined occupational skills and workplace-based cultural skills training for all middle-skilled occupations in Switzerland. They focus on the labor market transition of young immigrants (including refugees) from developing countries after completing upper secondary vocational education and training. Using administrative data of the full Swiss population, they show that graduating from dual programs—combining both occupational and workplace-based cultural skills—significantly increases their employment probabilities compared to graduating from purely school-based programs, teaching only occupational skills. Overall, their study suggests that the large effect of the Powercoders program, with the same dual skills training, also extends to refugees with different educational backgrounds and qualification levels.

One might argue that the selectivity of Powercoders limits its broader applicability, as it differs for example from the large-scale ALMP studied in Scandinavian countries (Arendt, 2022; Dahlberg et al., 2020). However, the selectivity of the Powercoders program may not be

a limitation but is likely the key feature of its effectiveness. The program targets high-skilled refugees with strong overall skill profiles. Our study does not assess the impact of broad training programs for refugees in general, but rather evaluates a specialized intervention designed for a high-demand sector targeting selected refugees with the potential to meet these demands. While our findings may not generalize to broad, non-specific training initiatives, they provide important insights into how targeted refugee programs can effectively address labor shortages in host countries. This model—bridging the skill gap with targeted refugee integration—offers a scalable framework for designing similar interventions in other shortage occupations.

Second, the lack of long-term data on applicants' labor market outcomes prevents us from assessing how the initial effect of the training program develops over time. We recognize that the high program effect likely diminishes over time and results in a more modest long-term impact. Nonetheless, comprehensive literature reviews by Brell et al. (2020) and Fasani et al. (2022) underscore that labor market entry conditions of refugees strongly predict their future employment prospects. Thus, analyzing the short-term effects of refugee training programs market remains critical.

Our findings offer highly valuable insights for policymakers focusing on refugee integration. By promoting training that combines skills in high-demand sectors such as IT with workplace-based cultural skills, refugees can significantly improve their labor market prospects. Such programs not only help mitigate critical skills shortages in the host country's labor market but also play a crucial role in successfully integrating the growing number of refugees and migrants into their host countries.

Appendix

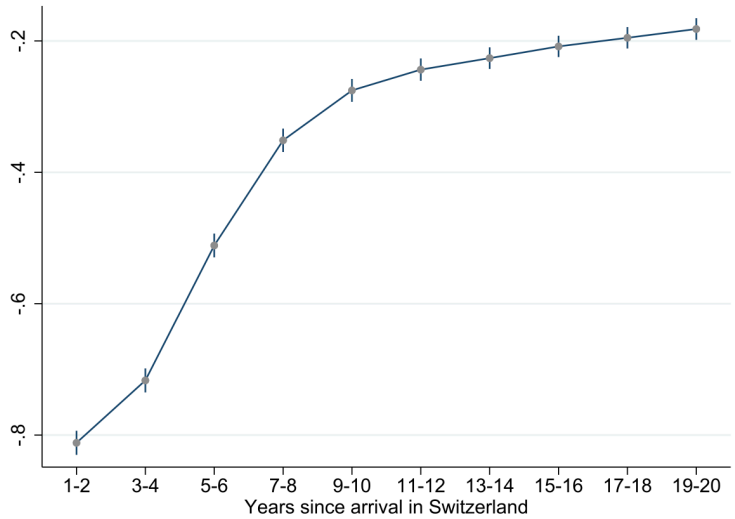

Fig. A.1 Employment probability: The native-refugee gap. This graph shows the native-refugee employment gaps by years since arrival in Switzerland. From "Labor market integration, local conditions and inequalities: Evidence from refugees in Switzerland" by Tobias Müller, Pia Pannatier, and Martina Viarengo (2023), World Development 170, p. 6., Copyright 2023 by Elsevier Ltd. Reprinted with permission.

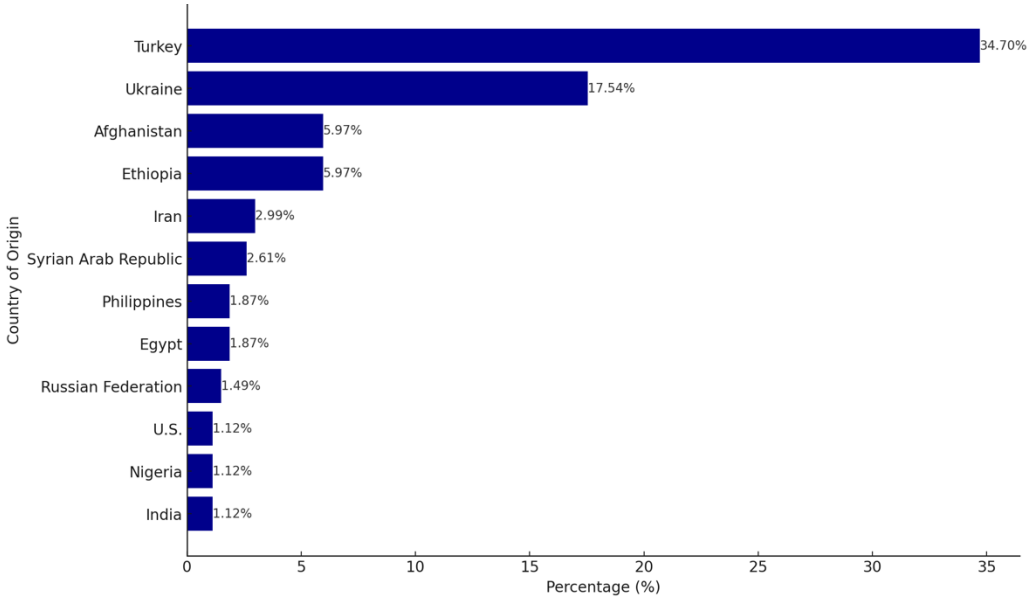

Fig. A.2 Top 12 countries of origin in the survey sample.
Notes: This figure covers respondents from a Fall 2023 survey of individuals who applied to the Powercoders coding and IT bootcamp in 2021, 2022, and 2023. The data reflects only the subset of applicants who responded to the survey.

Table A.1
Summary statistics – Refined sample 1 (Interview stage)

	Treatment Group (Participants)	Control Group (Non-Participants)		
	Mean	Mean	t-test	N
age	37.463	36.681	-0.781	140
	(6.372)	(5.494)	(-0.76)	
male	0.580	0.441	0.140	140
	(0.497)	(0.501)	(1.39)	
alternative IT program	0.492	0.523	0.0304	140
	(0.504)	(0.505)	(0.31)	
IT work experience (binary)	0.308	0.250	-0.0577	140
	(0.465)	(0.438)	(-0.65)	
IT work experience (in years)	1.869	1.534	-0.335	140
	(4.334)	(4.206)	(-0.40)	
Upper secondary degree	0.025	0.034	0.009	140
	(0.156)	(0.183)	(0.32)	
Bachelor's degree	0.407	0.373	-0.035	140
	(0.494)	(0.488)	(-0.41)	
Master's degree	0.235	0.220	-0.014	140
	(0.426)	(0.418)	(-0.20)	
Education 'IT'	0.173	0.153	-0.020	140
	(0.380)	(0.363)	(-0.32)	
Education 'Business, Administration, and Law'	0.148	0.136	-0.013	140
	(0.357)	(0.345)	(-0.21)	
Education 'Engineering'	0.161	0.153	-0.008	140
	(0.369)	(0.363)	(-0.13)	

Notes: This table refers to respondents from a Fall 2023 survey of individuals who applied to the Powercoders coding and IT bootcamp in 2021, 2022, and 2023. The data reflects only the subset of applicants who responded to the survey and were admitted to the final stage in the application process. Standard deviation in parentheses. Column 3 shows the t-test results, with t statistics in parentheses. Additionally, to account for potential correlations between the error terms of the separate regressions for the background characteristics, we conducted seemingly unrelated regressions (SUREGs). The SUREGs yield no significant differences in the background characteristics between the treatment and control groups, thereby confirming balance (the chi-squared statistic is 6.89 with a p-value of 0.549).
* p<0.05, ** p<0.01, *** p<0.001

Table A.2
Summary statistics – Refined sample 2
(Applicants close to the admission cutoff on the interview stage)

	Treatment Group (Participants)	Control Group (Non-Participants)		
	Mean	Mean	t-test	N
age	37.557	37.210	-0.346	38
	(6.262)	(5.570)	(-0.17)	
male	0.364	0.519	-0.0952	38
	(0.505)	(0.509)	(-0.44)	
alternative IT program	0.429	0.524	0.0952	38
	(0.535)	(0.512)	(0.42)	
IT work experience (binary)	0.286	0.286	0.000	38
	(0.488)	(0.463)	(0.00)	
Upper secondary degree	0.000	0.037	0.037	38
	(0.000)	(0.193)	(0.63)	
Bachelor's degree	0.364	0.519	0.155	38
	(0.505)	(0.509)	(0.85)	
Master's degree	0.182	0.222	0.040	38
	(0.405)	(0.424)	(0.27)	
Education 'IT'	0.182	0.148	-0.0337	38
	(0.405)	(0.362)	(-0.25)	
Education 'Business, Administration, and Law'	0.091	0.185	0.0943	38
	(0.302)	(0.396)	(0.71)	
Education 'Engineering'	0.091	0.222	0.131	38
	(0.302)	(0.424)	(0.93)	

Notes: This table refers to respondents from a Fall 2023 survey of individuals who applied to the Powercoders coding and IT bootcamp in 2021, 2022, and 2023. The data reflects only the subset of applicants who responded to the survey and who performed close to the cutoff on the final stage in the application process (interview). Standard deviation in parentheses. Column 3 shows the t-test results, with t statistics in parentheses. Additionally, to account for potential correlations between the error terms of the separate regressions for the background characteristics, we conducted seemingly unrelated regressions (SUREGs). The SUREGs yield no significant differences in the background characteristics between the treatment and control groups, thereby confirming balance (the chi-squared statistic is 3.35 with a p-value of 0.910). * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table A.3
Program participation and workplace-based cultural skills

	I Understanding Swiss business customs	II Understanding how to solve conflicts	III Understanding punctuality and deadline rules	IV Understanding hierarchies and authorities	V Understanding and adhering comfortable to ethical principles	VI Ability to navigate social interactions comfortably
Bootcamp participation	0.302**	0.280**	0.465***	0.291**	0.197	0.236*
	(0.133)	(0.133)	(0.131)	(0.133)	(0.133)	(0.133)
Controls	No	No	No	No	No	No
R-square	0.0173	0.0149	0.0411	0.0161	0.00739	0.0106
Observations	295	295	295	295	295	295

Standard errors in parentheses. The dependent variable is workplace-based cultural skill in standard deviation units. Independent variable is coding bootcamp participation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4
Program participation and workplace-based cultural skills (with control variables)

	I Understanding Swiss business customs	II Understanding how to solve conflicts	III Understanding punctuality and deadline rules	IV Understanding hierarchies and authorities	V Understanding and adhering comfortable to ethical principles	VI Ability to navigate social interactions comfortably
Bootcamp participation	0.374**	0.350**	0.381**	0.358**	0.191	0.245
	(0.161)	(0.163)	(0.150)	(0.162)	(0.156)	(0.155)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.274	0.256	0.361	0.268	0.316	0.304
Observations	285	285	285	285	285	285

Standard errors in parentheses. The dependent variable is workplace-based cultural skill in standard deviation units. Independent variable is coding bootcamp participation.
Controls: Age, gender, nationality, educational background (field), highest degree obtained.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5
Robustness check: Employment probability - Refined sample regressions controlling for interview score

	Refined sample 1 (Interview stage)	Refined sample 2
	I	II
Dep var.	Employed	Employed
Bootcamp participation	0.538***	0.479**
	(0.101)	(0.232)
Controls	Yes (Scores stage 1,2 & 3, cohort)	Yes (Scores stage 1,2 & 3, cohort)
R-square	0.305	0.262
Observations	140	38

Standard errors in parentheses. The dependent variable is employed as a binary variable.
Independent Variable: coding bootcamp participation. Model I comprises all applicants who reached application stage 3, i.e., those who had an interview with Powercoders. Models II includes applicants who reached stage 3 and who received scores close to the admission threshold.
Controls: scores on application stage 1, 2, and 3, cohort
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6
Lee Bounds - Lower Bounds

	Initial Sample		Refined Sample 1 (Interview Stage)		Refined Sample 2	
	I	II	III	IV	V	VI
Dep Var.	Employed	Employed	Employed	Employed	Employed	Employed
Bootcamp participation	0.348*** (0.056)	0.409*** (0.098)	0.370*** (0.075)	0.346*** (0.085)	0.394** (0.171)	0.392* (0.214)
Controls	No	Yes (all)	No	Yes (Scores stage 1,2 & cohort)	No	Yes (Scores stage 1,2 & cohort)
R-square	0.0871	0.414	0.151	0.161	0.129	0.209
Observations	406	268	140	140	38	38

Standard errors in parentheses. Worst case scenario assumption: All non-respondents in the control group have the best employment outcome. The dependent variable is a binary variable indicating employment, constructed by randomly reassigning non-respondents in the control group as employed (lower bound).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7
Lee Bounds - Upper Bounds

	Initial Sample		Refined Sample 1 (Interview Stage)		Refined Sample 2	
	I	II	III	IV	V	VI
Dep Var.	Employed	Employed	Employed	Employed	Employed	Employed
Bootcamp participation	0.592*** (0.049)	0.721*** (0.078)	0.556*** (0.070)	0.555*** (0.080)	0.579*** (0.141)	0.563*** (0.181)
Controls	No	Yes (all)	No	Yes (Scores stage 1,2 & cohort)	No	Yes (Scores stage 1,2 & cohort)
R-square	0.269	0.585	0.312	0.323	0.319	0.351
Observations	406	268	140	140	38	38

Standard errors in parentheses. Best case scenario assumption: All non-respondents in the control group have the worst employment outcome. The dependent variable is a binary variable indicating employment, constructed by randomly reassigning non-respondents in the control group as not employed (upper bound).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8

Distribution of Interview Rating Results

Interview Rating	Number of applicants	Percent	Cumulative
0	6	4.29	4.29
100	5	3.57	7.86
133	2	1.43	9.29
167	8	5.71	15.00
200	7	5.00	20.00
233	11	7.86	27.86
267	8	5.71	33.57
300	19	13.57	47.14
333	28	20.00	67.14
367	28	20.00	87.14
400	18	12.86	100.00
Total	140	100.00	

Notes: This table refers to respondents from a Fall 2023 survey of individuals who applied to the Powercoders coding and IT bootcamp in 2021, 2022, and 2023. The data reflects only the subset of applicants who responded to the survey and were admitted to the final stage in the application process. The interview rating ranges from 0 to 400, where 0 indicates non-participation or lack of progress, 1–100 denotes below-expectation performance, 101–200 represents an average rating, 201–300 corresponds to good performance, and 301–400 reflects outstanding performance. Applicants with a score of 300 or higher were admitted to the program.

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