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Farzana Afridi
Indian Statistical Institute and IZA

Rachel Heath
University of Washington

Tanu Gupta
University of Southampton Delhi

Kanika Mahajan
Ashoka University

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Smart Skilling: Experimental Evidence on Vocational Training Design*

We study how the design of vocational skill training programs impacts labor market outcomes, including occupational choice. Women applicants to skill training centres in India are randomized into either a vocational training (VT) program that combines sector-specific hard skills with on-the-job training, or VT plus Project-Based Experiential Learning that incorporates digital skills (VTP), or a control group which is not enrolled into any skill training. Almost a year after the start of the intervention, the nature of employment shifts towards the women's preferred sector, leading to higher self-employed work and earnings therein. These positive effects are observed only for the VTP group, whose usage of social media for business purposes increases due to the intervention. At the same time, satisfaction levels of women assigned to VTP training rise on multiple dimensions. Our findings highlight the role of complementary sector-specific skills in enhancing the impact of vocational training.

JEL Classification: J24, J44, J62, I31

Keywords: vocational skilling, digital skills, on-the-job training, self-employment, women, India

Corresponding author:
Farzana Afridi
Indian Statistical Institute
Economics and Planning Unit
7, S.J.S. Sansanwal Marg
New Delhi 110016
India
E-mail: fafridi@isid.ac.in

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1 Introduction

While there are factors on both the supply and the demand side that keep women from joining the labor force (Heath et al., 2024), one policy focus has been on job training programs and their potential for strong effects on women's employment and subsequent upward mobility in the labor market (McKenzie, 2017; Fox and Kaul, 2018; Kluve et al., 2019; McKenzie et al., 2021).[1] However, the large literature on job training programs often shows mixed results, for both overall effects and differential impacts on women (McKenzie, 2017; McKenzie et al., 2021). One key factor that can potentially determine training program effectiveness—and thus help explain these mixed results—is the design of the training program itself. Design could potentially be very important, given a large literature on education that shows how modality matters (Banerjee et al., 2016; Gray-Lobe et al., 2022), with experiential learning showing particular promise (Harris et al., 2015; Bharti et al., 2024). Yet, there are few studies that identify the causal effects of *what* to deliver in job training programs to make them more effective.

We design and evaluate different vocational training programs to improve labor market outcomes of women, by implementing an individual-level randomized intervention in India that includes a control group and two treatments: vocational training (VT) focuses on sector-specific (beauty and wellness) hard skills with on-the-job training (total duration of 5 months) and VT with an additional Project-Based Experiential Learning (PBEL) component of 2 weeks that focuses on digital skills and basic soft-skills required for the sector (VTP).[2] Recent qualitative evidence suggests that digital skills can be a high-leverage area when paired with market relevant curricula (UNESCO, 2018 and G20 Research Group, 2017). The

[1] Globally, women's labor force participation lags behind men's by about 26 pp (ILO, 2018). For instance, in urban India, 27% women aged 18-40 are employed as compared to almost 80% men (Periodic Labor Force Survey, 2023). Women, in low and middle income countries especially, confront several challenges in their economic engagement ranging from educational gaps, limited networks to social norms that limit mobility and access to salaried jobs.

[2] Digital skills include digital literacy and awareness, navigating social media platforms for professional purposes and job search through online platforms. Soft skills include communication, professional conduct, customer service, time management and personal finance.

PBEL component focused on women's digital literacy might have particularly strong effects in developing country contexts where there is much promise for digital skills to improve labor market outcomes (Horton et al., 2017; Kässi et al., 2021), but women frequently lag men in digital literacy (World Bank, 2021).[3]

The vocational training was implemented in the cities of Delhi and Bangalore, major metropolitan areas in India, with a total sample of almost 2000 women. Starting from June 2023 to April 2024, each training batch with approximately 40 women applicants were surveyed at baseline and then individually randomized into either VT, VTP or the control group (not offered any skill training). This sample of women across all batches had expressed interest in enrolling for the beauty-sector related skilling program at baseline, were followed up and resurveyed approximately 10 months after their respective batch start date. Our training intervention had high take-up and completion rates. Compliance with the treatment assignment was 87% or higher in both treatment arms. Importantly, the completion rates in both skilling arms was more than 75%. The overall attrition at endline was very low at 5%, with no differential attrition across treatment arms overall or in treatment interacted with baseline demographics.

Almost a year since the start of their training batch, we find that women assigned to the VTP arm are more likely to be currently employed than those assigned to the VT program, although vocational training did not have a significant effect on either treatment group's overall employment relative to the control group. VTP women shift sectors: they are 3.8 pp increase more likely to be self-employed than the control group, a shift that is driven by a 3.6 pp shift towards their preferred beauty and wellness industry. These effects are both significantly higher than the effects in the VT group. Using assignment to treatment as an instrument in a 2SLS specification to estimate treatment effects on compliers, we estimate that VTP increased preferred sector employment by 9 pp.

[3] In India, for instance, the Multiple Indicator Survey (MIS) shows that in 2021, 31% of women in urban India aged 15-24 could find, download and install software, whereas 37% of men in the same demographic group could do so. Women even face difficulties in very basic digital skills such as copying or pasting files or folders, sending emails, or transferring files (UNICEF, 2023).

Our analysis shows that higher probability of employment is accompanied by an increase in the intensity of work (hours worked) and improvement in returns to work (earnings) for the VTP group relative to VT and to the control group. Women in the VTP group worked 2.34 days more and earned INR 1071 more in the previous three months, relative to the control group. These estimated effects are also significantly higher than for the VT group ($p<0.05$). Overall, these findings indicate that incorporating PBEL in sector-specific job training programs affects both participants' success in finding employment but also developing entrepreneurial skills that allow them to find a job in their preferred sector, that is both more remunerative and flexible.

Note that the VTP training program included two additional components: digital skills and non-digital soft-skills. Digital skills can be very useful in providing beauty and wellness services since social media can be used for outreach to a larger base of potential customers or enable higher engagement with online job search or gig work platforms. Indeed, we find a significant increase of 7.5 pp in the usage of social media for business purposes by women in the VTP arm relative to women in both the control and the VT groups. At the same time, we do not find any positive effects of VTP on confidence and self-efficacy measures, suggesting that non-digital soft-skills provided in the training are unlikely to have exclusively driven the observed positive gains in employment for the VTP group. This suggests that the digital skill training was critical in improving women's labor market outcomes and their entrepreneurial ability. Women in the VTP program were not only more likely to be self-employed in the beauty industry but they also worked more hours and earned higher income in this sector, relative to the VT arm.

Our study finds that the intervention led to significantly higher overall satisfaction of women in the VTP group, relative to both the control group and the VT group. Specifically, providing digital skills strongly enhanced satisfaction with own current skill levels, and marginally improved satisfaction with the financial well-being of own household. We do not find any differential effects on decision making within the household, gender attitudes, and mobility due to training. Given the positive impacts on labor market outcomes along with higher satisfaction in VTP, the results indicate that economic empowerment of women positively impacted their psycho-social well-being. Interestingly, however, the VTP did not lead to higher job aspirations or confidence, suggesting that these are not necessary for training to improve life satisfaction.

A cost-benefit analysis of the VTP module shows that combining PBEL training with sector-specific hard skills, is economically viable. Our estimates indicate that the full cost of VTP module can be recouped within ten years of continued employment, yielding an internal rate of return of this vocational training program of more than 11%.

The finding that business-as-usual VT skill training did not improve labor market outcomes in our context is supported by research which shows that improved human capital may not always increase labor supply, especially amongst women whose overall labor supply is lower. For instance, the causal effect of education on women's labor supply is not always positive (Heath and Jayachandran, 2016). Theoretically, while productivity increases should lead to greater chances of working, higher search costs for more specialized jobs can actually lower labor supply in the short run. This effect can be exacerbated if job training creates unrealistic expectations (Groh et al., 2016b; Acevedo et al., 2020). Indeed, we document negative impacts of VT alone on several measures of satisfaction, earnings expectations, confidence in having necessary skills, and self-efficacy, suggesting frustration. But importantly, we also point out that the addition of relevant digital skills through the VTP program provides enough of a positive productivity effect leading to net positive labor market outcomes.

Our study makes three key contributions to the growing literature on job training programs, especially among the youth and women. First, by documenting heterogeneity in outcomes within the same experimental context, our study indicates that the what and how of training delivery is a key driver of the observed heterogeneous impacts of vocational training. We show that vocational training that combines hard skills with complementary digital skills can enhance access to freelance economy work, where online platforms are crucial, such as in beauty and wellness services. These skills are especially important for entrepreneurs to improve client outreach, as they enable better utilization of digital platforms, social media, and other online applications. Our findings indicate that bridging the gender gap in skills can improve women's work opportunities. Moreover, our findings show that targeted skilling can help individuals shift to preferred occupations, potentially increasing their tenure in the labor market. Unlike much of the extant literature that focuses on moving unemployed youth into any job, our intervention was not limited to unemployed women. It aimed both to raise employability and to facilitate sectoral transitions through upskilling.

We argue that the content and format of the VTP created an environment where these skills could pay off for training participants. Existing studies find mixed impacts of vocational training on employment outcomes (see Agarwal and Mani (2024) and McKenzie (2017) for a review) in different contexts and with varying characteristics of the training programs.[4] In contexts where studies find limited effects for women, gender-specific barriers to employment—such as childcare and family obligations (Cho et al., 2013; Shonchoy et al., 2018; Barrera-Osorio et al., 2023) or a lack of safe and convenient transportation to training opportunities (Field and Vyborny, 2022)—can potentially explain the low take-up, completion and employment effects for women. In contrast, our training centres were close to women's residential location, ensuring high take-up and completion rates. The sector-specific focus of the training also ensured strong linkages with the demand for beauty and wellness services, which also allow for self-employment opportunities within or close to women's homes.

Second, to the best of our knowledge, our study is the first to show the causal effects of digital skills on work opportunities and entrepreneurship, specifically for women. Recent studies of programs that provide 'hard' vocational skills combined with on-the-job training or stipends, in combination with 'soft' (non-digital) skills that focus on improving confidence,

[4] While sustained positive impacts on employment have been documented in India (Maitra and Mani, 2017), Uganda (Bandiera et al., 2020; Alfonsi et al., 2020), Liberia (Adoho et al., 2014) and Bangladesh (Das, 2021) of about 4-7 pp, Attanasio et al. (2017) do not find any difference in employment rates for trainees although their earnings were 12% higher ten years after training, due to increase in formal employment, largely driven by young women. Conversely, Alzúa et al. (2016) in Argentina, Barrera-Osorio et al. (2023) in Columbia, and Groh et al. (2016a) in Jordan, find insignificant or limited impacts on women trainees.

leadership, communication, teamwork, grit and financial literacy (Acevedo et al., 2020; Bandiera et al., 2020; Das, 2021; Barrera-Osorio et al., 2023), find mixed evidence on the role of these skills in improving labor market success. Typically, entrepreneurial training in low and middle income countries involve record-keeping, marketing, and planning. These are often shown to produce only moderate gains in business practices and sometimes in sales (Valdivia, 2015; De Mel et al., 2014). Some studies that vary content innovations—such as simplified "rules-of-thumb" financial heuristics (Drexler et al., 2014; Arráiz et al., 2019), personal-initiative mindsets (Campos et al., 2018), tailored empowerment modules (Bulte et al., 2017)— show that these additional components can yield larger and more persistent returns, especially when they address entrepreneurs' baseline constraints or cognitive barriers. A handful of studies that integrate soft-skills, one-on-one coaching, or grant support alongside core training show some success in improving women's entrepreneurial outcomes (Calderon et al., 2020; McKenzie and Puerto, 2021). We contribute to this literature by demonstrating that the key additional component to hard skills training can be digital skills, particularly among workers seeking self employment in the services sector.

Finally, our paper establishes a link between economic empowerment and psycho-social well-being via vocational skills. While Maitra and Mani (2017) find no effect of vocational training on Indian women's empowerment and happiness, Adoho et al. (2014) find that providing livelihood and life skills to adolescent girls in Liberia increases self-confidence and lowers anxiety. Additionally, Bandiera et al. (2022) find a sharp decline in teen pregnancy and age of marriage after vocational training. We show that on one hand, effective training (the VTP, in our case) can improve well-being and satisfaction on multiple dimensions, while on the other, training that does not materialize into improved labor market outcomes (the VT, in our case) can actually worsen psychological well-being.

In the next section we outline the background and context of our study. Section 3 provides details of the study design and intervention. The data and methodology for estimating impacts are discussed in Section 4. We outline the results and potential mechanisms in

Sections 5 and 6, respectively. Section 9 concludes.

2 Background and context

Despite rapid economic growth since the 1990s, declining fertility (World Bank, various years), and an increase in the education of women in India over the past three decades, the workforce participation rate for women in India continues to remain low.[5] In urban India, it has remained stagnant at 25-32% for the last three decades compared to 93% for men (Klasen and Pieters, 2015).[6] Self-employment dominates the nature of work done by both women and men in urban India – constituting almost 40% of total employment. Importantly, the share of self-employment for women in urban India has increased from 33% in 2017 to 41% in 2023 (PLFS, 2017 and 2023). This has been accompanied by an increase in the proportion of micro-enterprises owned by women from 20% in 2015-16 to 26% in 2023.[7] While most of these tend to be own-account enterprises[8], higher female enterprise ownership is shown to eventually create a "multiplier" effect for female employment (Chiplunkar and Goldberg, 2024).[9]

Survey studies in urban areas indicate a strong preference for self-employed work by women, which is often home-based, by both women themselves as well as their husbands or families in India (e.g. Afridi et al. (2023b)). Women in India frequently enter self-employment

[5]While there is some evidence of increasing labor force participation over the past five years (The Economist, 2024), India still remains at outlier compared to other countries with similar levels of GDP.

[6]Previous studies highlight the role of various factors in explaining both the decline in rural India and the stagnation in urban India - low market returns to women's work, along with lack of 'good' jobs for women vs the higher returns to home production as their education increases (Afridi et al., 2018), falling demand for women's labor in agriculture due to mechanization and lack of suitable alternative jobs for women which can be done near home (Afridi et al., 2023a), limited information networks (Calvo-Armengol and Jackson, 2004; Mortensen and Vishwanath, 1994; Afridi et al., 2023b), and restrictive social norms (Field et al., 2016). One aspect that remains under-explored is the role of skills in explaining the persistent gender gap in employment.

[7]Authors' own calculations from Unincorporated Enterprise Surveys Survey (UNES) 2015 and Annual Survey of Unincorporated Sector Enterprises (ASUSE) 2023.

[8]An own-account enterprise is an unincorporated, non-farm business operated by a single self-employed person (the "own-account worker") without any hired employees.

[9]This is because female entrepreneurs enjoy a relative advantage in hiring women. Thus, policies that lower expansion costs after entry not only boost the growth of women led firms but further raise female employment by generating additional employment for women.

because it provides the flexibility to balance income generation with household and care-giving responsibilities, often through home-based work that offer flexibility and circumvents mobility and social constraints (Afridi et al., 2023b; Ho et al., 2024). Flexible, home-based roles, thus serve as a gateway to paid employment and can shift gender attitudes. In the services sector, which is the focus of this intervention, 44% of women's enterprises are home-based (dominated by tailoring and beauty & wellness enterprises), versus 26% for men (Shetty, 2018). However, lack of skills is shown to be an important constraint facing women entrepreneurship in India (Field et al., 2010) along with access to capital (Carranza et al., 2018).

Although the proportion of the working-age population that has undergone some vocational training has increased in recent years, it remains low, particularly for women. In 2023, only 28% of women and 49% of men aged 18-45 had undergone formal or informal vocational training. The Information Technology Enabled Services (ITES) sector formed the largest field where 30% of women and 36% of men underwent training. The other fields were quite distinct due to the perceived gender stereotypes in the labor market. For instance, textiles, beauty, health, and office related clerical work were among the top skills women acquired. For men these included: electronics, clerical work, mechanical engineering, civil engineering, and healthcare.

Along with vocational skills, stark gender disparities in digital skills also exist in India. While 55% of adult men have ever used the internet, only 33% of women ever have (NFHS 2019). These gender gaps exist among the youth as well. For instance, the Annual Survey of Education Research (ASER) 2024 finds that while 70% of boys aged 14-16 could perform basic smartphone tasks – setting an alarm, browsing for information, locating and sharing a YouTube video – 62% of girls in this age group were adept at these digital tasks. Importantly, only 30% of India's social-media users are female (Global Digital Report, 2024), suggesting that limited digital skills constrain women's ability to leverage social media for commercial purposes.

3 Experiment Design

We implemented our study in collaboration with Labournet Services, a nation-wide vocational skills training service provider that links individuals to work opportunities. Labournet aims at both social as well as productivity impacts, and hence focuses on enhancing the work opportunities of individuals from low-socioeconomic status backgrounds across multiple sectors: manufacturing, construction, leather, beauty and wellness, data entry, tailoring, and more. Our study focuses exclusively on creating work opportunities for women in the beauty and wellness sector through vocational skilling.

To recruit participants into its training program, Labournet advertises the program through channels such as sharing pamphlets and door-to-door visits in localities within 5-kms of the training centre, and through its alumni network. For our study, the mobilization began around 10-15 days before the baseline survey start date for a given batch. Women interested in receiving beauty and wellness related training completed a short application mentioning their age, education, marital status, religion, caste, address, and phone number, and were screened for eligibility.[10] Given the constraints on batch size for classroom training (around 25-30), eligible applications for a batch were capped at 40.

Following the baseline survey of individual applicants in each training batch, individual applicants were randomized into three groups – only vocational training, vocational training plus PBEL, and a control group (neither vocational training nor PBEL). Women randomized into treatment did not pay for any component of the vocational training, which was funded by corporations in the beauty and wellness industries. Appendix Figure A.1 explains the randomized treatment at the individual level within each training batch.

The intervention involved imparting hard skills, and a combination of digital and soft-skills. The hard skills training was delivered through classroom based learning and on-the-job training (total duration of 5 months). Digital and soft-skills were delivered through a Project-

[10]The eligibility criteria required applicants to be aged 17–35 and to have completed at least class 10 education. However, sometimes it was not strictly implemented by the field team. Hence, we ended up with 3 women aged less than 17 and 5 aged more than 35 in our baseline sample.

based Experiential Learning (PBEL) format (2 weeks). We, therefore, have two treatment arms – (a) VT – standard training offering only the hard-skills curriculum (b) VTP – enhanced training which offers the same core hard-skills curriculum plus a PBEL module.

Thus there are several key distinguishing elements of the design of our training program. First, the location of the training centres and strategy of mobilization by location leads to high take-up of training by those offered enrolment. Second, Labournet's low-cost training model, due to partnerships with sector-specific private corporates who subsidize the training costs, minimizes any financial constraints in training take-up by candidates. Finally, we layer on an additional feature of imparting digital and soft skills on to the usual hard skills training curriculum. We also provide suggestive evidence to disentangle the effects of digital vs soft-skill components of the VTP program.

We discuss the skilling curriculum of the VT and VTP programs in detail, next.

3.1 The Intervention

3.1.1 Vocational Training (VT)

The vocational training (VT) program spanned over five months, which included two months (189 hours) of classroom-based training instruction delivered through a combination of face-to-face classes, self-learning, and project-based activities, followed by three months of on-the-job training (OJT). Appendix Table A.1 Panel A provides a breakdown of the modules covered in VT during classroom training and the hours dedicated to each module.

(a) Face-to-face classes: These sessions focused on instructor-led demonstrations and hands-on practicals, which help candidates acquire skills through observation and guided practice.

(b) Projects: Candidates were involved in practical, real-world tasks that required critical thinking, problem-solving, and creativity of the students.

(c) On-the-job training (OJT): Following classroom training, candidates worked in salons where they applied their skills in a real-world setting. OJT helped candidates apply their theoretical knowledge gained from classroom training and hone their skills under professional supervision. These internships were primarily unpaid.[11]

3.1.2 Vocational Training Plus (VTP)

In addition to the VT training described above, women assigned to the VTP arm received an additional 76 hours of training of the PBEL module, focusing on digital and soft-skills. Panel B of Appendix Table A.1 provides a breakdown of the PBEL course-content and the hours dedicated to each sub-module. We describe these briefly below:

(a) Digital skills (28 hours): Candidates acquired proficiency in using technology, focused on the use of mobile devices, digital safety, and social media, making them capable of developing a digital portfolio to showcase their skills.

(b) Communication skills (21.5 hours): Learned effective communication skills required to excel in the workplace, including verbal, non-verbal, and written communication techniques.

(c) Organizational skills (11 hours): Focused on goal setting, professional behavior and conduct, and work ethics.

(d) Financial literacy (6.5 hours): Focused on budgeting, savings, and personal finance management.

(e) Time management (4.5 hours): Focused on prioritizing tasks, setting goals, planning and scheduling, delegating, and managing interruptions and distractions.

(f) Personal grooming (4.5 hours): Focused on how to present themselves professionally and on personal hygiene.

[11] The 63 women reported receiving an average of stipend INR 3350 over the entire duration of the OJT while 19 reported paying a fee for the OJT.

Of the approximately 40 women applicants in each batch, 30 were randomly offered vocational training, and 10 formed the control group. Within the 30 trainees, half received only the vocational curriculum (VT), and half received the vocational curriculum plus PBEL (VTP). The women applicants randomized into the control group were not offered enrolment into any vocational training program by Labournet Services.

The study was conducted at five Labournet centres in Bangalore and two in Delhi (see Appendix Figures A.2 and A.3 for centre location) across 57 batches— 19 in Delhi and 38 in Bangalore. The study batches started in June 2023 up until April 2024. Table A.2 shows the number of batches included in the study every month by city.

At baseline, and before the start of the vocational training, all 40 women applicants in each batch were surveyed to collect detailed information on their individual and household characteristics, including aspirations, life satisfaction and other measures of psycho-social well-being. Our final baseline sample comprises 1,956 women – 689 in Delhi and 1,267 in Bangalore. In total, 742 women were assigned to VT, 739 to VTP, and 475 to the control group at baseline.[12]

Women assigned to the treatment arm in each cohort underwent five months of technical skills instruction, while VTP participants completed the additional PBEL modules during the same period. The endline survey was administered approximately ten months after the training start date. To illustrate, Appendix Figure A.4 depicts the timeline for the training batch starting in June 2023 onwards.[13]

[12]Approximately 34 applicants per batch consented for the baseline survey.

[13]Mobilization and registration began about 10-15 days before the baseline survey, after which we finalized randomization and enrolment in June 2023. The baseline survey was completed before any training commenced. From June through November 2023, VT participants received five months of technical instruction, and VTP participants completed those five months plus 76 hours of PBEL. Finally, the endline survey was conducted approximately ten months after training began, i.e., in April 2024 for this cohort.

4 Data and Methodology

4.1 Data

4.1.1 Summary Statistics at Baseline

We collected baseline data on all 1,956 women in the baseline sample, from June 2023 and until April 2024, once they were mobilized for each batch but before the start of the training (see Appendix Table A.3 for variable definitions).[14] We report the overall descriptive statistics of our sample in Table A.4, column 1. Most candidates (87%) belong to Hindu households. A majority come from socio-economically disadvantaged groups – 31% identify as Scheduled Caste or Scheduled Tribe (SC/ST) and 47% as Other Backward Class (OBC). 15% of the women reside in female-headed households, and 70% of household heads have less than high school education.

Women in our sample are young. The average age of women in our study is 24 years. Less than half (43%) are married, and only 26% have at least one child under five in their household. Nearly all women have completed at least high school but less than 9% have ever completed any formal or informal skill training. The majority of women in our study were not working; only 16.5% of women are employed at baseline. Notably, current employment was not used as a criterion by our training partner—as long as the woman displayed interest in working in beauty sector.[15] Unconditional (conditional) on employment status, women report an average of 9.4 (51) work days and INR 3,785 (20,736) in earnings over the previous three months. In terms of digital usage, women report an average of three hours per day on mobile phones or the internet, primarily for entertainment purposes, while few respondents

[14]For brevity, we restrict our main analyses to variables included in the balance tests later, based on the pre-analyses plan.

[15]Our interviews with women trainees at Labournet show that knowing other women who worked in this sector generated their own interest. In addition, ability to work from home, ability to choose timings and family acceptance of the work are some of the important reasons they preferred working in the beauty sector. Typically, starting beauty services does not require much investment if carried out from home or at clients' homes. Procuring beauty products is a major expense that can be obtained for INR 25,000-40,000. Estimates available online are also similar (Registerkaro, Khatabook).

have experience with digital platforms or tasks for professional purposes.[16]

Table 1 presents the key household and individual characteristics for the control group (column 1) and for each treatment arm, VT and VTP (columns 2 and 3, respectively). Columns 4, 5, and 6 indicate whether these characteristics differ jointly across the control versus VT, control versus VTP, and VT versus VTP groups, respectively. The overall F-statistic for each comparison is low and statistically insignificant (last row), demonstrating that the key characteristics are balanced across groups.[17]

4.1.2 Compliance to Intervention

We obtained individual-level enrolment, attendance and completion records from Labournet for every enrolled candidate in both VT and VTP. Table 2 summarizes take-up, completion, and attendance rates for all women in our study. Around 88% of those assigned to VT and 87% of those assigned to VTP actually enrolled for the Labournet training program. These initial take-up rates are higher than the reported average of 70% in the literature (Agarwal and Mani, 2024). Within the VTP arm, 50.3% of assigned candidates enrolled in PBEL. As expected, no one in the control or VT arms took up the PBEL component. However, 11.8% of control-group participants also enrolled in the VT program.

Ultimately, 79.6% of the VT arm completed the VT training and in the VTP arm, 76.3% completed the VT training and 40.6% completed both the VT and PBEL trainings. One potential reason for the relatively high compliance in our study, as mentioned previously, is that on average the mean distance from applicants' homes to their assigned training centre was under 5 km (Appendix Figures A.2 and A.3). Further, Appendix Table A.6 shows that probability of completion is higher for women who are residing closer to the centre by 7.5 pp (column 2). This is in line with existing literature that shows higher take-up when training

[16]Appendix Table A.5 compares our sample with women in Karnataka and Delhi from the nationally representative PLFS 2023–24 (aged 18-35). Relative to the PLFS, our respondents are younger, have lower educational attainment, are more likely to be unmarried, and are less likely to be employed. They also disproportionately belong to disadvantaged social groups and Hindu households.

[17]Only small, marginally significant (at 10 percent level) differences are observed for household religion and education.

centres are located closer to trainees who are offered enrolment (Jain et al., 2019). The attendance rates were also high with average VT class attendance was 55.3% among VT participants and 53.3% among VTP participants.

Within the VTP, the average PBEL session attendance rate was lower at 32.6%. This is mainly attributable to the timing of the PBEL program rather than lack of candidate interest. Specifically, PBEL attendance was lower in the initial batches because the in-person PBEL sessions were scheduled after both VT classroom and OJT sessions. Since OJT often led to candidates' final placements, many were reluctant to attend PBEL sessions, as doing so required them to be on leave from their OJT internships. Consequently, PBEL sessions were rescheduled by Labournet in subsequent batches to follow directly after the VT classroom sessions but before the OJT training, improving PBEL attendance rates from September 2023 onwards.[18]

4.1.3 Attrition

The endline surveys were conducted almost 10 months after the batch start date for each cohort. We were unable to survey only 99 women from the baseline sample, yielding a 5% attrition rate. This is considerably below the 15% or higher attrition typical in skill training literature (Agarwal and Mani, 2024). Further, this rate is similar across the three groups - standing at 4.8% for control and 5.1% for the VT and VTP groups. Appendix Table A.7 examines whether attrition is differential across arms and by baseline candidate characteristics. The dependent variable takes a value of one if an individual attrited from our sample and zero otherwise. We find no significant differences in attrition rates across the three study arms (column 1). When we control for all baseline covariates simultaneously (column 2), we find that only married women are less likely to attrit. Interacting these covariates with treatment assignment (column 3) shows the joint F-statistic on interaction terms is not significant (p=0.24), indicating that attrition does not differ by baseline characteristics across

[18]To elaborate, the average PBEL session attendance rate was 29% for batches up to August 2023, but it increased to 35% from September 2023 onwards.

arms. Nevertheless, we check for robustness of our results to selective attrition later.

4.2 Estimation Strategy

We assess the impact of the design of vocational training on individual outcomes by estimating both the Intent-to-Treat (ITT) effects and the Treatment-on-the-Treated (ToT) effects using two-stage least squares. The ITT estimates capture the average effect of offering the intervention. The ToT estimates, by focusing on those who actually complete the training, reveal the direct causal effect of participation. Comparing ITT and ToT thus indicates the extent to which non-compliance influences overall program effectiveness. We compute the ITT effects on individual outcomes via the following ANCOVA specification:

$$Y_i = \beta_1 VT_i + \beta_2 VTP_i + \delta_c + \delta_t + Y_{i0} + X_i'\gamma + \epsilon_i \tag{1}$$

where Y_i is outcome for worker i in centre c in quarter-year t. VT_i and VTP_i are indicators for assignment to the vocational-only and vocational plus PBEL arms, respectively; δ_c capture centre fixed effects (differences in locational characteristics like instructors) and δ_t capture quarter fixed effects (seasonality in employment).[19] Y_{i0} is the baseline value of the outcome where available; and X_i is a vector of individual covariates (results remain unchanged when covariates are omitted). Since randomization occurs at the individual level, we report Huber–White robust standard errors. The parameters of interest, β_1 and β_2, show the causal impact of treatment assignment to each training arm on outcomes. Our primary outcomes measure labor-market attachment: current employment status, work status by category, work in the preferred beauty sector, days worked over the past three months, and earnings during that period. We also examine how the interventions affect days worked and earnings within each work category and specifically within the beauty sector.

In the ToT specification, we substitute treatment assignment with actual treatment completion to estimate its effect on individual outcomes. Completion is defined as a dummy

[19] Our conclusions are unchanged when we include month fixed effects to capture seasonality.

variable equal to one if a participant finishes VT or, in the case of VTP, completes the additional project-based experiential learning module regardless of VT completion. We then instrument completion with original assignment and report two-stage least squares estimates, which identify the causal effect of treatment uptake on outcomes. As a robustness check, we adjust for multiple hypothesis testing across our primary outcomes to ensure our inference remains valid.

5 Results

We discuss the impact of the intervention on women's labor market outcomes, heterogeneity of our findings and robustness to alternative specifications below.

5.1 Main Results

Figure 1 shows the current rates of employment—overall (Panel a), beauty sector (Panel b), self-employment (Panel c) and salaried employment (Panel d)—by group, across baseline and endline. These sample means suggest that the labor market outcomes improved between baseline and endline for all groups, but significantly more for the women assigned to the VTP group, specifically in the beauty sector and self-employed work. For instance, only 2% of women were engaged in beauty related work at baseline which increased to 8% for control, 9% for VT group and to almost 12% for VTP group at endline. Similarly, self-employment rates were around 6-7% at baseline, and increase to 10% for the control and VT group but to almost 14% for the VTP group at endline.

Furthermore, we examine which women transition into employment, and particularly self-employment, by endline. Figure 2 shows that nearly half of those who are self-employed at endline were already self-employed at baseline, while the other half were not employed at baseline.[20] Both overall employment and self-employment rates are higher in the VTP group

[20] Salaried workers at baseline generally remain salaried at endline, except in the control group, where a substantial proportion of salaried women are no longer working at endline.

than in the control group. [21] Next, we estimate Equation 1 for each outcome to confirm that these causal impacts persist when controlling for pre-specified observable characteristics.

Extensive margin: Table 3 reports ITT estimates in Panel A for our primary labor-market outcomes at endline, using Equation 1. We report the impact of the interventions on the probability of overall current employment, in beauty sector employment, and by type of employment (self-employment and salaried). We find no significant differences in overall employment rates across treatment and control groups (column 1), but women assigned to VTP are nearly 5 pp more likely to work than those in VT. Women assigned to VTP are also more likely to work in the beauty sector by 3.6 pp compared to control and 4.3 pp compared to the VT (column 2). By work type, VTP assignment increases probability of self-employment by 3.8 pp relative to control and by 2.1 pp relative to VT (column 3), with VT showing a small positive, but imprecise effect on self-employment. Column 4 finds that neither VT not VTP had a meaningful effect on salaried employment, consistent with its focus on skills that matter in particular for entrepreneurship in the sector of focus.

Panel B of Table 3 presents 2SLS (ToT) estimates by instrumenting training completion with random assignment to a treatment arm, addressing differential compliance. First-stage F-statistics are large (Appendix Table A.8), reflecting the high take-up rates discussed earlier. The ToT effects closely mirror the ITT findings: completing VTP increases the likelihood of working in the beauty sector by 9.0 pp and self-employment by 9.6 pp relative to control. In contrast, completing VT alone yields no significant gains in employment. Importantly, the VTP arm delivers significantly larger gains than VT in overall employment, beauty-sector employment and self-employment by almost 9 pp (p<0.05).

Work days and earnings: Table 4 presents the effects for days of work and earnings (in the past 90 days) by sector and type of work. These are coded as zero for those not

[21] We focus on the two largest occupation groups - salaried and self-employed - since casual employment is negligible in our context.

employed in the last 90 days and those who have not worked in a given type of work. Self-employed days increase by 3.20 in the VTP arm versus the control and 4.02 versus the VT arm. Earnings increase by 837 INR versus the control group (although this effect is not statistically significant), and 1900 INR versus the VT group (which is significant). Consistent with the findings in Table 3, the increase in days and earnings for the VTP arm are driven by employment in the beauty sector. We find an increase in days and earnings in the beauty sector for those offered VTP treatment relative to the control group by 2.34 days and INR 1071, respectively. The ToT estimates using 2SLS show similar results, with larger magnitudes.

The treatment effect on days worked (and earnings) for the VTP arm can reflect both an extensive-margin effect, since treatment increases the employment rate, and an intensive-margin effect, if treatment increases the days (or earnings) of those already employed. To disentangle these, we follow Carranza et al. (2022) and report the decomposed effects for the VTP arm in Appendix Table A.9.[22] We find that the intensive margin accounts for nearly 60% of the overall treatment effect on days worked, indicating that increased days worked by VTP participants, conditional on employment, drive most of the impact. In beauty sector employment, almost 90% of the gains in days worked and earnings stem from higher workdays and earnings among those employed in that sector, with only 10% attributable to a higher probability of employment in the beauty sector. Similarly, for self-employed work days, the gains are primarily driven by intensive-margin effects. These results show that VTP assignment significantly increased days worked and earnings among those employed, indicating greater work intensity and higher earnings quality post-treatment. We discuss the dimension of job quality later in more detail.

[22]The extensive-margin effect is calculated by multiplying the treatment effect on employment by the average days worked among control group candidates who are employed. The intensive-margin effect equals the total treatment effect on days minus the extensive-margin effect, isolating the change in days worked among employed treatment group candidates. The conditional effect is the implied mean change in days worked per employed treatment group candidate.

Occupation type: Our analysis indicates that the VTP intervention significantly shifted women to working in the beauty and wellness sector—a sector for which they revealed preference by registering for skill training with Labournet. Table 5 shows that the increase in probability of current employment, days worked, and earnings in the beauty sector are driven by self-employment increasing by 3.5 pp, 1.4 days, and INR 748, respectively, for the VTP assigned group relative to control (Panel A). Overall, these results suggest that the rise in both extensive and intensive margin of employment in the beauty sector for the VTP arm is driven by self-employed work. We find similar ToT estimates using 2SLS, which are reported in Panel B.

Quality of work: Did the labor market transition to self-employed work, induced by the VTP intervention, improve work quality? Nationally representative PLFS 2023–24 data show that women working as salaried employees in the beauty sector earn INR 45 per hour, whereas those who are self-employed earn INR 59 in profit per hour. In our two metropolitan cities, at baseline, women in salaried beauty roles earned INR 50 per hour, while those in self-employed beauty work earned nearly INR 174 per hour after business expenses.[23] Moreover, at baseline almost half of all self-employed beauty jobs are performed at home, whereas all salaried positions require working outside home. Thus, women shift toward more remunerative work within the beauty sector that can largely be done from home, for which women show a strong revealed preference (Jalota and Ho, 2023).

To assess whether work quality changed after treatment relative to control, we examine the effect of treatment on hourly wages. We assign zero values to women not engaged in any employment. Appendix Table A.10 presents results for both VT and VTP arms. VTP women earn 5.51 INR more per hour than control women, a 33% increase on the control mean, though the effect is not significant at traditional levels ($p = 0.166$). VTP women do earn significant more per hour (INR 10.60) in beauty sector work at endline than control women (column 2, row 1). Decomposition shows that nearly all of this increase reflects higher

[23]At endline, these figures rise to INR 51 per hour and INR 193 per hour, respectively.

wages among those employed in the beauty sector (INR 9.96 in column 2, row 3), rather than a higher probability of employment. In other words, VTP doesn't just allow women to switch sectors, it also facilitates higher paying self-employment. We likewise observe that VTP women experience higher gains in self-employed hourly wage rates, driven by intensive-margin effects (column 3). VT women also show a marginally significant hourly-wage gain of INR 5 when employed in the beauty sector (column 2, row 3).

Finally, we examine whether other job attributes like hours worked per work day, work location (outside home), and commute time differ by treatment and report the treatment effects along with decomposition of these effects in Appendix Table A.11.[24] While we find no significant differences for either training arm versus control for any of these attributes, VTP assigned women are significantly working fewer hours per work day and somewhat less likely to work outside the home when employed. None of the other job attributes like social security, health care, and paid leaves, differ by treatment. A very small proportion of workers get these benefits in our sample, whether salaried or self-employed, thus, it is not surprising that we find no difference in these job attributes across treatment groups.[25] Taken together, these results show that VTP assigned women who are employed at endline spend less hours per work day, and get higher wage per hour, leading to higher earnings, as compared to control. They are also more likely to work from home. Given the existing work shows that women value part-time work, and work from home, our results suggest that overall job quality measured by these attributes, becomes more favourable for employed women in VTP arm.

To summarize, the above results show that while there was no overall effect of treatment on employment, sector-specific skilling clearly shifts the nature of employment towards the preferred beauty sector for women. Within the sector, women are more likely to engage in self-employed work. The positive effects are driven by the VTP arm where women received both training in hard skills and project-based experiential learning which focused on imparting

[24]For all attributes, we assign zero value to women who are not working.

[25]Approximately 4% of women receive social security, and 2% report healthcare and paid leave benefits at their workplace. Thus, overall informality of work is quite high.

digital skills and basic soft skills. These results indicate that imparting complementary skills can be more effective than only the provision of hard skills in vocational trainings.

5.2 Heterogeneity

Self-employment generally requires some capital for materials and equipment, and thus may be undertaken primarily by women from wealthier households. In the beauty sector, however, work typically involves either operating from one's own home or travelling to clients' homes with minimal capital, hence, making it accessible even to less wealthy households. Moreover, women from less wealthy households often have fewer skills to begin with and limited access to alternative jobs, so they may benefit more from vocational training. To examine this, we classify households as wealthy if their baseline asset-index score exceeds the sample median. Panel A of Appendix Table A.12 shows that the positive effects of the VTP treatment on self-employment are concentrated among less wealthy households. Similarly, women in less wealthy households assigned to VT shift from salaried to self-employed work. Panel A of Appendix Table A.13 indicates that this increase is driven by self-employment in the beauty sector. Women from wealthier households do not experience gains from either training arm. Thus, the largest vocational-training benefits accrue to less wealthy women, and these benefits are similar across both arms—though slightly higher in the VTP arm.

Second, we collected locality level characteristics such as the distance to the nearest bus stop, because constraints like limited access to safe transportation can restrict employment gains for women (Field and Vyborny, 2022). Our data show that the bus is the most frequently used mode of transport among women in Bangalore and Delhi, as it is free for female riders in both states.[26] Female trainees likely use the bus to reach clients' homes, and clients to travel to nearby beauty parlours. Appendix Tables A.12 and A.13, Panel B, show that gains in self-employment in the beauty sector are driven by treated women living within half a kilometre of a bus stop. Additionally, gains that are twice as large for those assigned to the

[26] In our baseline survey, we asked employed women about their commute times and modes of transportation. Around 40% walked exclusively, and of those who used a transport service, nearly 70% took the bus.

VTP arm. The estimates indicate that VT and VTP assignments increase employment by 3 pp and 5.8 pp, respectively, for women in areas with better transport connectivity. Thus, although the effects are larger for VTP participants, VT trainees also benefit from improved transport connectivity.[27]

5.3 Robustness

We conduct several robustness checks to assess the validity of our main findings. First, we use the double post-lasso procedure developed in Belloni et al. (2014) to select the control variables, instead of directly introducing all baseline covariates in the regression and report the results in Appendix Table A.14 and A.15, Panel A. We continue to find positive and significant effects of training assignment in the VTP arm on employment driven by increased self-employment, days and earnings in the preferred beauty sector.

Second, we address concerns about false positives by applying the False Discovery Rate (FDR) procedure to adjust for multiple hypothesis testing. Panel B in Appendix Tables A.14 and A.15 report q-values for our main outcome variables. The results for probability of employment and days worked remain robust. This increases our confidence that the observed positive effects are not obtained purely due to chance.

Third, as discussed in Section 4 the overall attrition rate in our study is low at 5% and we do not find any differential attrition across arms or by respondent characteristics. Nonetheless, we check the robustness of our estimates by weighting our ITT estimates using inverse probability weights (IPWs). Panel C in Appendix Tables A.14 and A.15 presents IPW-weighted ITT estimates for primary employment outcomes at the extensive margin and employment outcomes for the beauty sector, respectively. The results remain consistent with the main findings estimates: the VTP arm continues to show significant improvements in the

[27] We also examined heterogeneity in training impact by age, marital status, education, having a child under age five, whether unemployed at baseline and caste but did not find any differential effects, hence, results are omitted for brevity. We find slightly higher gains for Muslim women in beauty related salaried work after VTP training. This is possible since beauty is a traditional occupation among Muslims and better networks may allow them to access limited jobs in the sector.

probability of self-employment and employment in the beauty sector and in self-employment work therein. This suggests that attrition does not bias our main results.

Fourth, we test whether a greater supply of trained women affects employment outcomes for the control group. If so, this would violate the Stable Unit Treatment Value Assumption (SUTVA), since some of the gains experienced by the treated participants may come at the expense of the control group. At the same time, a higher supply of trained women in a given sector can increase competition for a limited number of jobs, potentially reducing employment gains for treated individuals.

To examine both channels, we follow Ferracci et al. (2010) and Gautier et al. (2018) and assess whether the number of trainees influences endline outcomes in the control and treated arms.[28] We define trainee density as the number of women assigned to treatment within a two-kilometre radius of a woman's home in the same month that her training batch begins.[29] We then construct an indicator equal to one if the trainee density for a woman exceeds the sample median (11 trained women) and report heterogeneous effects in Appendix Tables A.16 and A.17. Additionally, we also control for the overall density of women who registered for the training program in the same radius within a woman's home in her training batch month. This allows for any differential effects on outcomes which may vary by overall population density in an area.

We find that the main effect of the above-median indicator is small and insignificant, indicating no effect of high trainee density on employment outcomes for the control group. However, women assigned to VTP in high treatment density localities show no employment

[28]For instance, Crépon et al. (2013) argue that job rationing can influence the impact of active labor market policies. To check this, they randomly assign the proportion of treated individuals across labor markets and find externalities only in locations where there is a large pool of unemployed workers at the same skill level. While our design does not randomly vary the treated proportion across locations, using the approaches of Ferracci et al. (2010) and Gautier et al. (2018), we can examine whether the number of trainees matters for employment rates in both control and treated groups.

[29]We choose this radius because most women prefer to work close to home. Our baseline data show that 40% of working women walk, and among those who use transport, 70% combine walking with bus travel or use only the bus. On average, they spend 15 minutes travelling one way, making a 2–3 km catchment reasonable. Note that we use crow-flying distance, which likely underestimates actual travel distances. Results are robust to 1 km and 3 km cut-offs.

gain relative to the control group, a pattern driven by a reduced likelihood of securing salaried jobs in the beauty sector. Thus, in markets where more workers receive training, the impact of vocational training on salaried employment is attenuated, presumably because trained women searched for jobs primarily within the beauty sector, leading to congestion. By contrast, trainee density does not affect beauty related self-employment (columns 1, 3, and 5 of Appendix Table A.17), the segment that exhibits a clear positive effect from VTP training. These results suggest that vocational training alone may be insufficient to increase salaried employment without matching demand, but geographically localized demand-side constraints matter less for self-employment among trained women.

6 Mechanisms

What explains the divergent labor market outcomes between the VT and VTP groups? First, we suggest that the PBEL component of the VTP program enhanced the effectiveness of the business-as-usual hard skills training provided in VT curriculum. Second, within the PBEL component, our results are driven by the digital skills imparted during VTP training. Lastly, we provide evidence against channels other than these digital skills—such as improved job information availability through strengthened networks—through which PBEL could have affected labor outcomes.

Given that we do not have a treatment arm that is PBEL only, our intervention is not designed to formally test the impact of PBEL alone on labor market outcomes. However, in Panel D of Appendix Tables A.14 and A.15 we redefine VTP participation as completion of both the VT and the PBEL components and redo the 2SLS analysis. Our results are now (insignificantly) larger in magnitude than the ToT results where we define compliers as those who complete the PBEL component, irrespective of completing the VT component (Panel B of Tables 3-5). This provides suggestive evidence that skills imparted in the PBEL component are likely to be complementary to hard skills and enhance the effectiveness of vocational training.[30] This is in line with the findings in Groh et al. (2016b), the only study which has an 'only soft-skills' treatment arm (among individuals not already endowed with sector-specific hard skills, as in Adhvaryu et al. (2018)) finds no effect of these skills on employment outcomes in Jordan. Based on our discussions with sector specialists within Labournet, it is unlikely that only the provision of PBEL would be effective without imparting any hard-skills since basic technical knowledge is imperative in the beauty and wellness sector.

Next, we provide evidence that the VTP effects were primarily driven by digital skills which were the dominant component of the PBEL curriculum. Consistent with this hypothesis and the VTP's focus on digital skills, Table 6 shows that VTP women are 7.5 pp more likely to use social media for business compared to both the control group and VT participants, suggesting that social-media use for marketing seems to drive the self-employment gains of the VTP group.[31] Furthermore, we do not find any significant, positive effects of VTP on measures of self-confidence and self-efficacy, suggesting that additional non-digital soft-skills component of PBEL are unlikely to have exclusively driven the positive gains in employment for this group (Appendix Table A.18).[32] We discuss these outcomes in more detail in the next section.

Finally, we rule out other alternative explanations driving the differing outcomes between the VT and VTP groups and also shed light on why we observe insignificant increase in employment for the VT group below:

Job search behavior: First, we examine whether provision of PBEL training altered job-search behavior, including modes of search, of candidates. It is possible that women with

[30]Note that 65 women in the VTP treatment completed the PBEL training but not the VT training, while 221 completed both VT and PBEL. When we re-estimate the ITT impact excluding these women, the ITT estimates are unchanged. While this result should be interpreted with caution given that the sample is selected, it is consistent with complementarity between VT and PBEL components.

[31]By contrast, we find no significant effects on gig platform registration, days worked, or earnings. Note that since we did not capture gig-work outcomes at baseline, we benchmark estimates against the endline control-group mean.

[32]The soft-skills training components focused on providing communication, financial and organizational skills. We do not find significant impacts on women's ability to open a bank account, pay utility bills, manage emergency situations or communicate more effectively, at endline.

better digital skills use more online modes of job search that are potentially more efficient and result in higher job offers. Notably, formal job search was low at baseline—only 12 percent had actively looked for work. In this context, if training increases search efficiency and/or narrows the list of sectors participants choose to search in, it could either increase overall search effort (if participants search more when it's more effective) or decrease overall search effort (if participants narrow their focus to the beauty sector or learn to search more quickly).

Appendix Table A.19 shows that VT women are 3.7 pp less likely to have searched for work in the past 90 days and received 0.03 fewer offers (a large point estimated compared to a control mean of 0.05), though neither effect is statistically significant. This suggestive evidence of reduced search is not consistent with greater search efficiency, but instead suggests that unsuccessful attempts at gaining preferred sector employment may dampen their propensity to search. Meanwhile, VTP trainees show some evidence of increased likelihood of online search (0.012 pp on a control mean of 0.04) and job applications submitted (0.11 on a control mean of 0.22), consistent with the VTP's focus on digital skills, though these estimates too are not statistically significant. Overall, therefore, there is no clear evidence that greater search effort is a key driver of improved labor outcomes in the VTP vis-a-vis VT group – though it is hard to discern patterns amongst the noisy estimates, and it is possible that the search that did take place was more effective and targeted.

Job search opportunities: Relatedly, we find in column (5) of Appendix Table A.19 that both VT and VTP participants view neighborhood job opportunities as worse than the control group. Although the VT effect is borderline significant, it is of very similar magnitude and statistically indistinguishable from the VTP effect, implying that training may narrow women's search to beauty jobs and worsen their perceptions of available work if these jobs are limited in supply. Together, these findings suggest that both the VT and VTP groups of trained women likely narrowed their search to the beauty sector, where demand did not increase in the short-run. Faced with limited jobs, while VTP participants had the skills to start self-employed work, those in the VT arm were unable to do so.

Job networks: Lastly, if VTP strengthened networks due to more hours of in-class training, we would expect to see treatment effects of sources of job information; Appendix Table A.20 examines traditional referrals, online platforms, institutional contacts, and media (like newspapers or pamphlets). We do not find any significant differences in the types of job information sources across treatment arms, suggesting that network effects are unlikely to be driving our results, particularly since the PBEL component implied only 76 hours of additional training.[33]

In summary, the findings suggest that VTP's digital-skill component helps women pivot into self-employment and use technology for business purposes, whereas VT alone may narrow search without providing sufficient new skills to improve salaried employment outcomes. This provides suggestive evidence of complementarity of sector-specific hard skills and digital skills in explaining the findings in our context.

Overall, there are three key take-aways from our randomized evaluation of the delivery and design of vocation skilling: (1) our high training completion rates show that location of skill training centres is an important component of training design; (2) business-as-usual training (in our case, VT) is unlikely to yield labor market returns unless these programs combine hard-skills with new-age digital and soft skills modules; and (3) bridging the digital-gender divide can help women transition to gainful self-employment in low-income settings.

7 Downstream effects

In this section we assess whether assignment to skill training affected other aspects of women's lives and their family members.

[33]Skilling take-up, completion rates, and average attendance in the VT component are also similar across VT and VTP groups, suggesting that differential participation is unlikely to explain the difference in outcomes.

7.1 Psycho-social well-being of participants

Did vocational training and the subsequent labor market effects impact women's psycho-social well-being, such as satisfaction with their education, skills, and life as a whole? We construct indices for satisfaction and other measures of well-being following the methodology in Kling et al. (2007) based on the sub-components captured for each measure.

Table 7 presents the ITT estimates on the satisfaction index and its sub-components by the treatment arms in Panel A and ToT estimates using 2SLS in Panel B. The ITT estimates in column 1 show that women offered VTP training report higher satisfaction compared to the control group, with an increase of 0.056 standard deviation. This impact is also significantly higher relative to the VT group (p<0.05), with a borderline significant (p=0.138) reduction of 0.046 standard deviations in the VT arm. Notably, the estimates in columns 2-7 show that higher satisfaction in VTP assigned women is driven by higher satisfaction with both their current skill level and their household's current financial situation compared to the control and VT arms. VTP assigned women also report greater satisfaction with the work they are currently doing when compared to VT group. Meanwhile, women in VT group report significantly lower satisfaction with their current education level and work than the control group. It appears that higher employment in their desired sector leads to higher satisfaction in the VTP arm, while frustration with the VT treatment not leading to these outcomes leads to lower satisfaction.[34]

We also assess impacts on the confidence of women in undertaking tasks and in their skills, job aspirations (expected salary, undertaking work outside home, undertaking full-time work and willingness to work in the next two years), ability to undertake decisions within the household, mobility outside home, decision-making and measures of self-efficacy. As mentioned previously, Appendix Table A.18 shows the ITT estimates on these indices. The

[34]While we tried to emphasize that selection for the additional PBEL component was random (so that respondents in the VT group did not take their lack of selection as a judgement on their ability), we cannot rule out the possibility that VT women might have felt demotivated because they were not selected for the additional training, causing some of the negative effects on their psycho-social well-being.

estimates are small and insignificant for women in the VTP training. While this may seem to be a surprising null result given labor outcomes in the VTP group, note that the participants in the study were a group of already relatively empowered urban women, as illustrated by volunteering for training at baseline, and there might not have been much scope to increase these outcomes. Meanwhile, women offered VT training report lower job aspirations and self-efficacy compared to the control group and the VTP arm.[35]

To summarize, the above results show that VTP training programs have a positive impact on several of women's psycho-social well-being outcomes. Women assigned to VTP training report higher satisfaction, driven by higher satisfaction with their current skill level and household financial situation. This highlights that women may get better job opportunities and better incomes after gaining digital skills. As a result, they also feel more satisfied with their skills and their household's financial situation. This shows that combining sector-specific hard skills with relevant digital skills that enhance customer outreach, can improve women's psycho-social well-being via improved labor market outcomes.[36]

7.2 Spillovers to other family members

Another relevant question is whether the participants' experience in VT and VTP training affected other household members. Recall from Table 3, that VT women are, if anything, less likely to hold regular salaried positions or to be employed at endline. However, in Appendix Table A.21, we find that other female household members in VT households (i.e. excluding the participant) increase both their extensive (participation) and intensive (hours, earnings) labor supply. There is also an increase in hours and earnings for male members, but it is

[35] ITT estimates for sub-components of job aspirations, confidence, decision-making, mobility, self-efficacy, and gender attitudes, respectively show insignificant impacts across any treatment arms, except for job aspirations and self-efficacy. For job aspirations, women assigned to the VT arm report lower salary expectations relative to control and VTP groups, while both VT and VTP are less likely to prefer to work outside the home relative to control. The former is in line with the VT group not being able to access jobs and hence lowering expectations, while the latter shows that flexibility provided by the beauty sector to work from home through self-employed work may be internalized by trainees, hence, their preferences could have shifted. These results are available on request.

[36] The labor market and well-being results are unchanged when we control for baseline responses to the standard Marlowe-Crowne module that measure an individual's tendency to give socially desirable responses.

imprecise. Compensation could be driving these results: if the family needs money and one household member is not working while looking for a job, then another household member works instead. This compensation could be concentrated among women if their lower baseline labor supply gives them more scope to work more. Another possibility is that women in the VT arm do learn valuable skills which they share with (female) family members who put these skills to work in other sectors while the VT participants delay labor market entry until they find a job opportunity in their preferred sector.

8 Cost-Benefit Analysis

To evaluate the cost-effectiveness of our intervention program we calculate the welfare gains using net present value (NPV) estimates of non-labor and labor market outcomes affected by the skilling program. Table 8 shows these estimates for VTP group relative to control group. These estimates capture the broader welfare effects of VTP training program, rather than presenting the standard IRR calculation based on wage earnings alone.

Panel A in Table 8 shows the per trainee total cost for VTP training of INR 36,517 (≈ USD 440), which comprises: (1) actual training costs (INR 2570 ≈ USD 31); and (2) the opportunity cost of attending training for 5 months (proxied by the average monthly earnings of the employed women at baseline, and assuming unpaid OJT internships). The training costs include both fixed costs, such as infrastructure, curriculum design, administration and other variable costs, including trainer compensation and consumables.

Panel B evaluates non-labor market benefits from increased satisfaction reported by VTP participants, as many women are now working in their preferred sector. We monetise this increased satisfaction at INR 398 annually based on the valuation estimated by HM Treasury (2021), which generates NPV of INR 4960 over 20 years of working life (column 1).[37]

Panel C shows the estimated labor market returns. Although the overall earnings do not increase due to VTP, our estimates show that women in the VTP arm have higher earnings

[37] The assumptions we make to monetise satisfaction are laid out in Appendix B.

in the beauty sector, which is welfare-improving, especially given occupational preferences. These short-term gains may compound into longer-term benefits if women exhibit greater longevity in the labor market and work more intensively due to employment in their preferred sector. Women in the VTP arm earned INR 1,071 more over three months – equivalent to INR 4,284 annually. Assuming constant marginal effect of trainings over time,[38] the NPV of incremental earnings equal INR 53,388, assuming 20 years of work in the labor market (column 1). Combining these estimated labor market returns with non-pecuniary gains in Panel B, gives a benefit-cost ratio of 1.60 and an IRR of 11.3% (Panel C, column (1)) relative to no training. Column (2) and (3) extends the analysis to 25 and 30 years of remaining productive life, showing the benefit-cost ratio at well above one and IRR estimates that remain high.

Taken together, these findings demonstrate that the VTP training program generates high returns when we include these psycho-social benefit. These findings place our estimates within the broader range of cost-effectiveness evaluations in the vocational training literature. The full cost of VTP can be recovered within approximately ten years of sustained employment. This recovery period compares favorably with several existing skilling interventions (viz. Maitra and Mani (2017), Giné and Mansuri (2014)).[39]

9 Conclusion

In this study, we assess the role of skilling in addressing the low levels of labor force participation and quality of work. We design a randomized intervention in two cities in India to analyze the relevance of sector-specific hard skills and a combination of hard skills with

[38]Theoretically, the effects of the training could increase over time if the material learned is complementary to experience, or decrease, if the control group will eventually develop the skills on their own. The mixed long term effects of training we discuss in section 1 are consistent with the effects of some trainings increasing over time and others decreasing.

[39]Maitra and Mani (2017) estimate that the costs of a tailoring training program in India can be recouped in less than four years with continuous employment. Giné and Mansuri (2014) report training costs of approximately USD 146 per participant in Pakistan and find modest labor market returns that justify the investment. In contrast, Cheema et al. (2019) estimates substantially higher cost of USD 286 per participant for a tailoring and market linkage program, with a projected payback period exceeding two decades.

digital skills, in improving women's work opportunities. Specifically, we provide a vocational training (VT) program in the beauty sector which includes classroom and on-the-job training components. In another treatment group, along with the VT program, we incorporated Project-Based Experiential Learning (PBEL) that focused on digital skills which are specific to professional success in this sector.

If anything, the VT training alone had negative effects, leading to lower (though statistically insignificant) rates of employment, and decreases in some measures of life satisfaction. We argue that the VT module alone lead to increased desire to work in the respondents' preferred beauty sector, but without tools to find jobs, respondents grew frustrated. Adding the PBEL component, however, lead to improvements in women's outcomes, with the nature of employment shifted towards the preferred beauty sector and self-employed work therein, and higher measures of life satisfaction. We show evidence that the additional effect of the PBEL was driven by the digital skills taught there, which led to greater usage of social media for business purposes and some increase in online modes of job search.

However, our results should not be interpreted to suggest that digital skills training alone can improve women's labor market outcomes. While we cannot formally test the complementarity of the hard skills provided in the VT with the digital skills provided by PBEL, it seems logical that digital skills per se may not be effective without sector specific hard-skills. Indeed, training programs that provide non-digital soft skills are likely effective among workers who are highly skilled already. Instead, our findings show that aligning skill training with specific sectors, with hands-on training or internships, which leverage knowledge of digital skills required in that sector, can significantly enhance both labor market outcomes and psycho-social well-being.

References

Acevedo, P., G. Cruces, P. Gertler, and S. Martinez (2020): "How vocational education made women better off but left men behind," *Labour Economics*, 65, 101824.

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

Adoho, F., S. Chakravarty, D. T. Korkoyah, M. K. Lundberg, and A. Tasneem (2014): "The impact of an adolescent girls employment program: The EPAG project in Liberia," *World Bank Policy Research Working Paper*.

Afridi, F., M. Bishnu, and K. Mahajan (2023a): "Gender and mechanization: Evidence from Indian agriculture," *American Journal of Agricultural Economics*, 105, 52–75.

Afridi, F., A. Dhillon, S. Roy, and N. Sangwan (2023b): "Social networks, gender norms and labor supply: Experimental evidence using a job search platform," *CAGE working paper*.

Afridi, F., T. Dinkelman, and K. Mahajan (2018): "Why are fewer married women joining the work force in rural India? A decomposition analysis over two decades," *Journal of Population Economics*, 31, 783–818.

Agarwal, N. and S. Mani (2024): "New Evidence on Vocational and Apprenticeship Training Programs in Developing Countries," *Available at SSRN 4851428*.

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

Alzúa, M. L., G. Cruces, and C. Lopez (2016): "Long-run effects of youth training programs: Experimental evidence from Argentina," *Economic inquiry*, 54, 1839–1859.

Arráiz, I., S. Bhanot, and C. Calero (2019): "Less is more: Experimental evidence on heuristic-based business training in Ecuador," *Inter-American Development Bank, Development through the Private Sector Series.*

Attanasio, O., A. Guarín, C. Medina, and C. Meghir (2017): "Vocational training for disadvantaged youth in Colombia: A long-term follow-up," *American Economic Journal: Applied Economics*, 9, 131–143.

Bandiera, O., N. Buehren, R. Burgess, M. Goldstein, S. Gulesci, I. Rasul, and M. Sulaiman (2020): "Women's empowerment in action: evidence from a randomized control trial in Africa," *American Economic Journal: Applied Economics*, 12, 210–259.

Bandiera, O., A. Elsayed, A. Smurra, and C. Zipfel (2022): "Young adults and labor markets in Africa," *Journal of Economic Perspectives*, 36, 81–100.

Banerjee, A., R. Banerji, J. Berry, E. Duflo, H. Kannan, S. Mukherji, M. Shotland, and M. Walton (2016): "Mainstreaming an effective intervention: Evidence from randomized evaluations of "Teaching at the Right Level" in India," Tech. rep., National Bureau of Economic Research.

Barrera-Osorio, F., A. Kugler, and M. Silliman (2023): "Hard and soft skills in vocational training: Experimental evidence from Colombia," *The World Bank Economic Review*, 37, 409–436.

Belloni, A., V. Chernozhukov, and C. Hansen (2014): "Inference on treatment effects after selection among high-dimensional controls," *Review of Economic Studies*, 81, 608–650.

Bharti, N. K., S. Malik, A. Mukhopadhyay, and N. Prakash (2024): "Science on the Move: How Experiential Learning Shapes Human Capital," .

Bulte, E., R. Lensink, and N. Vu (2017): "Do gender and business trainings affect business outcomes? Experimental evidence from Vietnam," *Management Science*, 63, 2885–2902.

Calderon, G., J. M. Cunha, and G. D. Giorgi (2020): "Business literacy and development: Evidence from a randomized controlled trial in rural Mexico," *Economic Development and Cultural Change*, 68, 507–540.

Calvo-Armengol, A. and M. O. Jackson (2004): "The effects of social networks on employment and inequality," *American economic review*, 94, 426–454.

Campos, F., M. Frese, M. Goldstein, L. Iacovone, H. C. Johnson, D. McKenzie, and M. Mensmann (2018): "Is personal initiative training a substitute or complement to the existing human capital of women? Results from a randomized trial in Togo," in *AEA Papers and Proceedings*, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, vol. 108, 256–261.

Carranza, E., C. Dhakal, and I. Love (2018): *Female entrepreneurs: How and why are they different?*, World Bank Washington, DC.

Carranza, E., R. Garlick, K. Orkin, and N. Rankin (2022): "Job search and hiring with limited information about workseekers' skills," *American Economic Review*, 112, 3547–3583.

Cheema, A., A. I. Khwaja, F. Naseer, and J. N. Shapiro (2019): "Glass walls: Experimental evidence on access constraints faced by women," .

Chiplunkar, G. and P. K. Goldberg (2024): "Aggregate implications of barriers to female entrepreneurship," *Econometrica*, 92, 1801–1835.

Cho, Y., D. Kalomba, A. M. Mobarak, and V. Orozco-Olvera (2013): "Gender differences in the effects of vocational training: Constraints on women and drop-out behavior," *World Bank Policy Research Working Paper*.

Crépon, B., E. Duflo, M. Gurgand, R. Rathelot, and P. Zamora (2013): "Do labor market policies have displacement effects? Evidence from a clustered randomized experiment," *The quarterly journal of economics*, 128, 531–580.

Das, N. (2021): "Training the disadvantaged youth and labor market outcomes: Evidence from Bangladesh," *Journal of Development Economics*, 149, 102585.

De Mel, S., D. McKenzie, and C. Woodruff (2014): "Business training and female enterprise start-up, growth, and dynamics: Experimental evidence from Sri Lanka," *Journal of Development Economics*, 106, 199–210.

Drexler, A., G. Fischer, and A. Schoar (2014): "Keeping it simple: Financial literacy and rules of thumb," *American Economic Journal: Applied Economics*, 6, 1–31.

Ferracci, M., G. Jolivet, and G. van den Berg (2010): "Treatment evaluation in the case of interactions within markets," Tech. rep., IFAU-Institute for Evaluation of Labour Market and Education Policy.

Field, E., S. Jayachandran, and R. Pande (2010): "Do traditional institutions constrain female entrepreneurship? A field experiment on business training in India," *American Economic Review*, 100, 125–129.

Field, E., S. Jayachandran, R. Pande, and N. Rigol (2016): "Friendship at work: Can peer effects catalyze female entrepreneurship?" *American Economic Journal: Economic Policy*, 8, 125–153.

Field, E. and K. Vyborny (2022): "Women's mobility and labor supply: experimental evidence from Pakistan," *Asian Development Bank Economics Working Paper Series*.

Fox, L. and U. Kaul (2018): "The evidence is in: How should youth employment programs in low-income countries be designed?" *World Bank policy research working paper*.

Fujiwara, D. and D. Dass (2021): "Incorporating life satisfaction in discrete choice experiments to estimate wellbeing values for non-market goods," *Simetrica-Jacobs Research Paper, July.*

Gautier, P., P. Muller, B. Van der Klaauw, M. Rosholm, and M. Svarer (2018): "Estimating equilibrium effects of job search assistance," *Journal of Labor Economics*, 36, 1073–1125.

Giné, X. and G. Mansuri (2014): "Money or ideas? A field experiment on constraints to entrepreneurship in rural Pakistan," *A Field Experiment on Constraints to Entrepreneurship in Rural Pakistan (June 1, 2014). World Bank Policy Research Working Paper.*

Gray-Lobe, G., A. Keats, M. Kremer, I. Mbiti, and O. W. Ozier (2022): "Can education be standardized? Evidence from Kenya," *Evidence from Kenya (September 16, 2022). University of Chicago, Becker Friedman Institute for Economics Working Paper.*

Groh, M., N. Krishnan, D. McKenzie, and T. Vishwanath (2016a): "Do wage subsidies provide a stepping-stone to employment for recent college graduates? Evidence from a randomized experiment in Jordan," *Review of Economics and Statistics*, 98, 488–502.

——— (2016b): "The impact of soft skills training on female youth employment: evidence from a randomized experiment in Jordan," *IZA Journal of Labor & Development*, 5, 1–23.

Harris, C. J., W. R. Penuel, C. M. D'Angelo, A. H. DeBarger, L. P. Gallagher, C. A. Kennedy, B. H. Cheng, and J. S. Krajcik (2015): "Impact of project-based curriculum materials on student learning in science: Results of a randomized controlled trial," *Journal of Research in Science Teaching*, 52, 1362–1385.

Heath, R., A. Bernhardt, G. Borker, A. Fitzpatrick, A. Keats, M. McKelway, A. Menzel, T. Molina, and G. Sharma (2024): "Female labour force participation," *VoxDevLit*, 11, 1–43.

HEATH, R. AND S. JAYACHANDRAN (2016): "The causes and consequences of increased female education and labor force participation in developing countries," Tech. rep., National Bureau of Economic Research.

HM TREASURY (2021): "Wellbeing Discussion Paper: Monetisation of Life Satisfaction Effect Sizes: A Review of Approaches and Proposed Approach," *HM Treasury, London.*

HO, L., S. JALOTA, AND A. KARANDIKAR (2024): "Bringing work home: Flexible arrangements as gateway jobs for women in west bengal," Tech. rep., STEG Working Paper.

HORTON, J., W. R. KERR, AND C. STANTON (2017): "Digital labor markets and global talent flows," Tech. rep., National Bureau of Economic Research.

ILO (2018): "World Employment and Social Outlook: Trends for Women 2018 – Global snapshot," Tech. rep., International Labour Organization, Geneva.

JAIN, T., P. MAITRA, AND S. MANI (2019): "Barriers to skill acquisition: Evidence from English training in India," *World Development*, 114, 314–325.

JALOTA, S. AND L. HO (2023): "What Works For Her? How Work-from-Home Digital Jobs Affect Female Labor Force Participation," *Job Market Paper*.

KÄSSI, O., V. LEHDONVIRTA, AND F. STEPHANY (2021): "How many online workers are there in the world? A data-driven assessment," *Open Research Europe*, 1, 53.

KLASEN, S. AND J. PIETERS (2015): "What explains the stagnation of female labor force participation in urban India?" *The World Bank Economic Review*, 29, 449–478.

KLING, J. R., J. B. LIEBMAN, AND L. F. KATZ (2007): "Experimental analysis of neighborhood effects," *Econometrica*, 75, 83–119.

KLUVE, J., S. PUERTO, D. ROBALINO, J. M. ROMERO, F. ROTHER, J. STÖTERAU, F. WEIDENKAFF, AND M. WITTE (2019): "Do youth employment programs improve labor market outcomes? A quantitative review," *World Development*, 114, 237–253.

Maitra, P. and S. Mani (2017): "Learning and earning: Evidence from a randomized evaluation in India," *Labour Economics*, 45, 116–130.

McKenzie, D. (2017): "How effective are active labor market policies in developing countries? a critical review of recent evidence," *The World Bank Research Observer*, 32, 127–154.

McKenzie, D. and S. Puerto (2021): "Growing markets through business training for female entrepreneurs: A market-level randomized experiment in Kenya," *American Economic Journal: Applied Economics*, 13, 297–332.

McKenzie, D., C. Woodruff, K. Bjorvatn, M. Bruhn, J. Cai, J. Gonzalez-Uribe, S. Quinn, T. Sonobe, and M. Valdivia (2021): "Training entrepreneurs," *VoxDevLit*, 1, 3.

Mortensen, D. T. and T. Vishwanath (1994): "Personal contacts and earnings: It is who you know!" *Labour economics*, 1, 187–201.

Shetty, N. (2018): "Exploring Barriers to Scale for Women Entrepreneurs in India," Ph.D. thesis, Harvard University.

Shonchoy, A., T. Fujii, and S. Raihan (2018): "Barriers to Labor Migration for the Rural Poor: Experimental Evidence from a Vocational Training Program in Bangladesh," *Available at SSRN 3395229*.

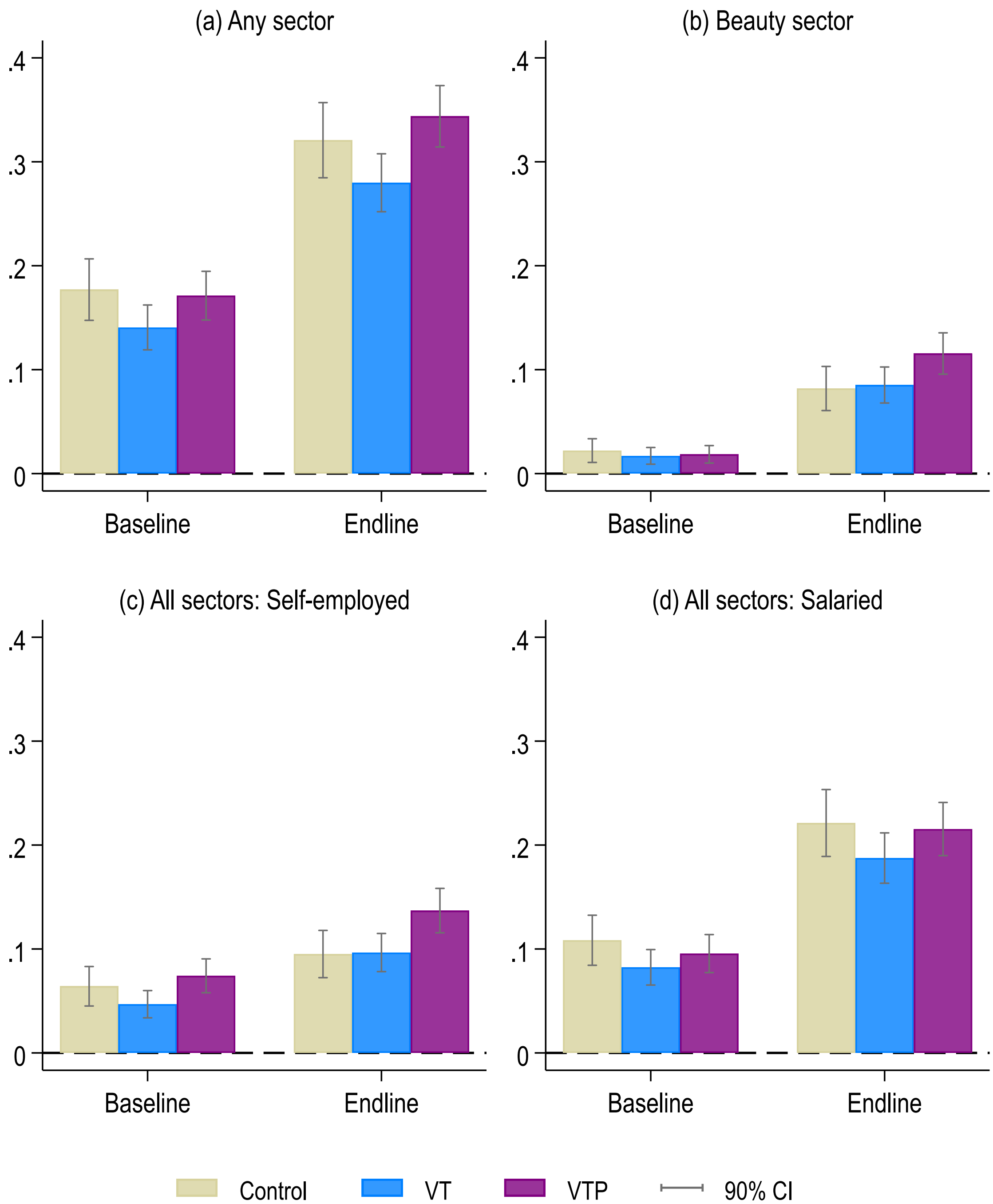
The Economist (2024): "The mystery of India's female labour-force participation rate," *The Economist*.

UNICEF (2023): "Bridging the gender digital divide: Challenges and an urgent call for action for equitable digital skills development," *UNICEF. Retrieved July*, 30, 2023.

Valdivia, M. (2015): "Business training plus for female entrepreneurship? Short and medium-term experimental evidence from Peru," *Journal of Development Economics*, 113, 33–51.

World Bank (2021): "Global Findex Database," *https://www.worldbank.org/en/publication/globalfindex*.

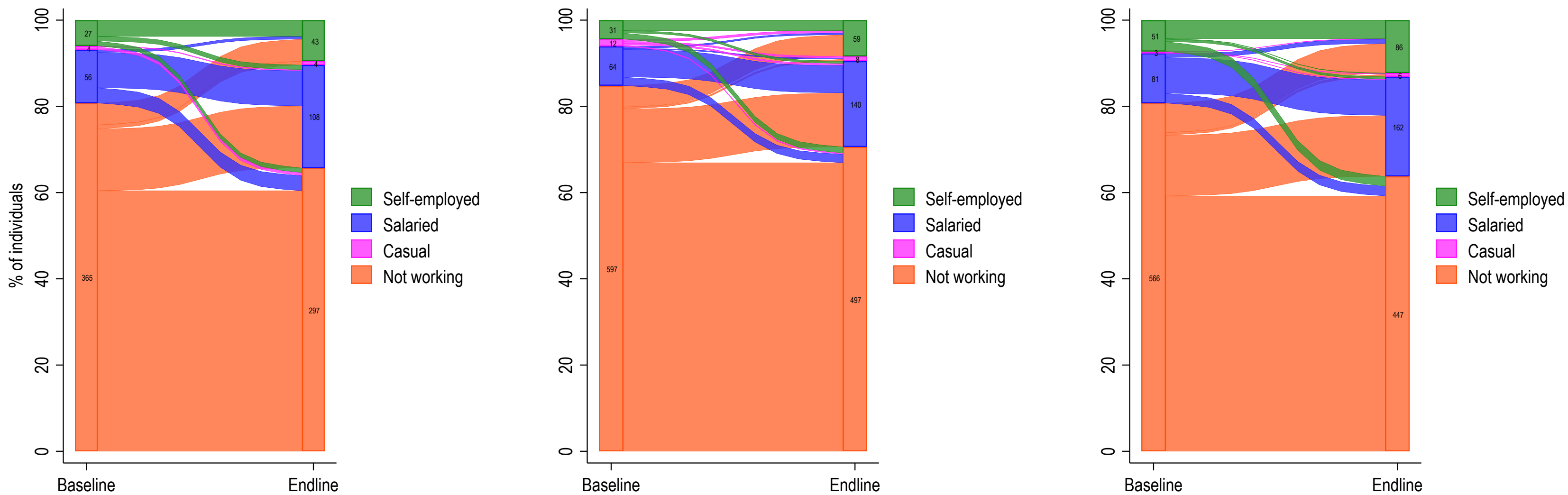
Figure 1: Average rates of current employment at baseline and endline



Note: The figures show the average rates of current employment in any sector, beauty and wellness sector, self-employed in any sector and salaried in any sector at baseline and endline, by treatment group. The sample size is 1,857.

Figure 2: Labor market transitions between baseline and endline

(a) Control (b) VT (c) VTP



Notes: The figure shows the transition between four occupation categories – not employed, employed in salaried work, casual work, and self-employed – between the last 90 days preceding the baseline survey date and the last 90 days preceding the endline survey date. Panel (a) shows the occupational transitions for the control group, Panel (b) for VT, and Panel (c) for VTP groups. In case a respondent reports more than one type of job, we assign the employment type that generated the maximum earnings in the last 90 days preceding the survey dates. The sample size for each occupation category is mentioned in the panels on the Y-axis.

Table 1: Balance on household and individual characteristics at baseline

Variable	Mean			OLS		
	C	VT	VTP	C vs VT	C vs VTP	VT vs VTP
	(1)	(2)	(3)	(4)	(5)	(6)
Household characteristics						
Hindu	0.882	0.881	0.850	0.002	-0.110	-0.067*
				(0.045)	(0.085)	(0.040)
ST and SC	0.318	0.310	0.299	0.001	0.010	0.005
				(0.040)	(0.080)	(0.037)
OBC	0.455	0.466	0.490	0.016	0.068	0.015
				(0.037)	(0.074)	(0.034)
HH head: Female	0.135	0.150	0.156	0.034	0.094	0.010
				(0.041)	(0.082)	(0.037)
HH head: High school education	0.149	0.158	0.156	0.022	0.027	-0.016
				(0.041)	(0.081)	(0.037)
HH head: College & above education	0.143	0.159	0.120	0.032	-0.075	-0.075*
				(0.043)	(0.092)	(0.041)
Number of under-5 children in HH	0.225	0.256	0.280	0.029	0.100*	0.014
				(0.030)	(0.059)	(0.026)
Asset index	0.016	0.036	-0.047	-0.000	-0.010	-0.005
				(0.010)	(0.019)	(0.009)
Individual characteristics						
Age	24.453	24.299	24.318	0.000	-0.006	-0.004
				(0.004)	(0.007)	(0.003)
High school education	0.457	0.468	0.448	0.013	-0.026	-0.022
				(0.034)	(0.067)	(0.031)
College & above education	0.208	0.218	0.199	0.013	-0.016	-0.021
				(0.042)	(0.084)	(0.039)
Currently married	0.425	0.414	0.441	-0.023	0.062	0.067
				(0.046)	(0.091)	(0.043)
Mobile phone/internet usage intensity	3.034	3.137	2.974	0.007	-0.007	-0.012
(hours in a typical day)				(0.008)	(0.017)	(0.008)
Previous skilling	0.091	0.077	0.091	-0.042	0.034	0.048
				(0.052)	(0.099)	(0.047)
Current employment	0.179	0.146	0.175	-0.032	-0.067	-0.019
				(0.101)	(0.172)	(0.085)
Days worked (90 days)	10.078	8.180	10.068	-0.000	0.003	0.002
				(0.002)	(0.003)	(0.002)
Earnings (Rs.) (90 days)	4262.540	3340.746	3923.473	-0.000	-0.000	-0.000
				(0.000)	(0.000)	(0.000)
N	475	742	739	1217	1214	1481
Prob >F				0.980	0.798	0.281

Note: SC: Scheduled Caste, ST: Scheduled Tribe, OBC: Other Backward Caste, HH: household. This table presents the average baseline household and individual characteristics across the control arm in column 1, the vocational training (VT) arm in column 2 and the vocational training along with project-based experiential learning arm (VTP) in column 3. The number of respondents in each arm is reported. Current employment is measured at the time of baseline survey. Days worked and earnings are calculated as the total number of days the respondent has worked for in the last 90 days preceding the baseline survey date and her total earnings in those 90 days. The calculation of days worked and earnings is unconditional on employment, i.e., for our calculation, we take the value 0 for days worked and earnings for those who were unemployed in the last 90 days preceding the baseline survey date. Appendix Table A.3 provides detailed definitions for the other variables. We test for differences in the average baseline household and individual characteristics across the control vs VT arm (column 4), the control vs VTP arm (column 5) and the VT vs VTP arm (column 6). Treatment arm assignment is the dependent variable. In column 4, it takes a value of 1 for VT and 0 for the control group. In column 5, it takes a value of 1 for the VTP group and 0 for the control group. In column 6, it takes a value of 1 for the VTP group and 0 for the VT group. The *p-values* associated with the joint significance test of all the characteristics are reported in the last row. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table 2: Compliance to intervention

	Control (1)	VT (2)	VTP (3)
Vocational Training (VT)			
% of women who took up training	11.8	88.3	87.1
% of women who completed training	9.7	79.6	76.3
Average attendance (%)	7.1	55.3	53.3
Project-Based Experiential Learning (PBEL)			
% of women who took up training	0.0	0.0	50.3
% of women who completed training	0.0	0.0	40.9
Average attendance (%)	0.0	0.0	32.6
N	475	742	739

Note: This table shows the proportion of women in our baseline sample, assigned to Control (column 1), VT (column 2) and VTP (column 3), who enrolled and completed the VT and PBEL components of the training, along with average attendance rates in each training component.

Table 3: Impact of skilling on labor market outcomes (extensive margin)

	Current employment			
	Sector		Type	
	Any	Beauty	Self-employed	Salaried
	(1)	(2)	(3)	(4)
Panel A: ITT				
VT	-0.025	0.007	0.011	-0.021
	(0.025)	(0.016)	(0.016)	(0.023)
VTP	0.029	0.036**	0.038**	0.004
	(0.026)	(0.017)	(0.017)	(0.023)
VT = VTP [p-value]	[0.015]	[0.056]	[0.081]	[0.204]
Panel B: 2SLS				
VT	-0.035	0.010	0.016	-0.030
	(0.035)	(0.022)	(0.022)	(0.032)
VTP	0.063	0.090**	0.096**	0.001
	(0.068)	(0.043)	(0.044)	(0.060)
VT = VTP [p-value]	[0.051]	[0.018]	[0.020]	[0.478]
N	1,857	1,857	1,857	1,857
Baseline Control Mean	0.18	0.02	0.06	0.11

Note: Panel A shows the ITT estimates for the effect of the treatment assignment on whether an individual was currently employed (column 1), whether the individual was employed in the beauty sector (column 2), whether the individual was self-employed (column 3), and whether the individual had regular/salaried employment (column 4) – at endline. Panel B shows the ToT estimates using 2SLS after instrumenting training completion with treatment assignment. Equality of the VT and VTP coefficients is tested and the associated *p-values* are provided in both the panels. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table 4: Impact of skilling on labor market outcomes (intensive margin)

	Days worked				Earnings			
	Sector		Type		Sector		Type	
	Any	Beauty	Self-employed	Salaried	Any	Beauty	Self-employed	Salaried
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: ITT								
VT	-0.821	0.179	0.428	-0.820	-1062.639	-19.148	-102.134	-935.220
	(1.648)	(0.889)	(0.849)	(1.553)	(936.160)	(512.938)	(552.688)	(807.470)
VTP	3.195*	2.335**	2.249**	1.315	836.818	1070.997*	304.782	508.222
	(1.726)	(1.010)	(0.962)	(1.581)	(1021.442)	(573.663)	(629.869)	(841.985)
VT = VTP [p-value]	[0.008]	[0.018]	[0.042]	[0.118]	[0.021]	[0.033]	[0.457]	[0.036]
Panel B: 2SLS								
VT	-1.178	0.245	0.600	-1.171	-1507.837	-30.857	-144.959	-1328.455
	(2.316)	(1.248)	(1.191)	(2.178)	(1318.899)	(719.395)	(776.118)	(1135.021)
VTP	7.499*	5.745**	5.614**	2.919	1675.253	2600.641*	705.702	915.139
	(4.532)	(2.620)	(2.493)	(4.166)	(2689.715)	(1491.999)	(1633.975)	(2224.670)
VT = VTP [p-value]	[0.012]	[0.008]	[0.013]	[0.185]	[0.108]	[0.025]	[0.504]	[0.165]
N	1,857	1,857	1,857	1,857	1,857	1,857	1,857	1,857
Baseline Control Mean	9.98	1.08	3.07	6.74	4,275.68	612.91	1,145.72	2,915.50

Note: Panel A shows the ITT estimates for the effect of the treatment assignment on the total number of days worked in the last 90 days (preceding the endline survey date) in any sector (column 1), in the beauty sector (column 2), in self-employed work (column 3), and in regular/salaried work (column 4); the total earnings in the same 90 days in any sector (column 5), in the beauty sector (column 6), in self-employed work (column 7), and in regular/salaried work (column 8). Panel B shows the ToT estimates using 2SLS after instrumenting training completion with treatment assignment. Equality of the VT and VTP coefficients is tested and the associated *p-values* are provided in both the panels. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table 5: Impact of skilling on labor market outcomes in the beauty and wellness sector

	Beauty & wellness sector					
	Current employment		Days worked		Earnings	
	Self-employed	Salaried	Self-employed	Salaried	Self-employed	Salaried
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ITT						
VT	0.015	-0.013	0.276	-0.281	149.321	-240.192
	(0.012)	(0.012)	(0.464)	(0.778)	(396.864)	(307.323)
VTP	0.035***	-0.003	1.421**	0.756	748.244*	238.945
	(0.012)	(0.012)	(0.558)	(0.864)	(431.996)	(389.906)
VT = VTP [p-value]	[0.095]	[0.324]	[0.041]	[0.168]	[0.161]	[0.122]
Panel B: 2SLS						
VT	0.021	-0.019	0.385	-0.401	207.978	-341.410
	(0.017)	(0.016)	(0.651)	(1.092)	(556.647)	(431.462)
VTP	0.091***	-0.012	3.554**	1.745	1871.471*	499.512
	(0.032)	(0.033)	(1.425)	(2.249)	(1115.247)	(1010.849)
VT = VTP [p-value]	[0.008]	[0.785]	[0.011]	[0.217]	[0.073]	[0.281]
N	1,857	1,857	1,857	1,857	1,857	1,857
Baseline Control Mean	0.01	0.01	0.36	0.67	264.82	316.59

Note: Panel A shows the ITT estimates for the effect of the treatment assignment on whether the individual was currently employed in the beauty sector in self-employed work (column 1), and in regular/salaried work (column 2) – at the endline; the total number of days worked in the last 90 days (preceding the endline survey date) in the beauty sector in self-employed work (column 3), and in regular/salaried work (column 4); the total earnings in the same 90 days in the beauty sector in self-employed work (column 5), and in regular/salaried work (column 6). Panel B shows the ToT estimates using 2SLS after instrumenting training completion with treatment assignment. Equality of the VT and VTP coefficients is tested and the associated *p-values* are provided in both panels. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table 6: Impact of skilling on usage of social media and gig work platforms

	Social media platform usage for work	Registered on service-oriented platforms	Employment through gig-work platforms	Days worked through gig-work platforms	Earnings through gig-work platforms
	(1)	(2)	(3)	(4)	(5)
VT	0.009	0.007	0.003	0.253	88.591
	(0.029)	(0.005)	(0.002)	(0.183)	(62.642)
VTP	0.075**	0.002	0.003	0.262	79.833
	(0.029)	(0.004)	(0.002)	(0.184)	(70.433)
VT = VTP [p-value]	[0.012]	[0.375]	[0.973]	[0.973]	[0.924]
N	1,857	1,857	1,857	1,857	1,857
Baseline Control Mean	0.42	0.00	0.00	0.00	0.00

Note: This table shows the ITT estimates for the effect of the treatment assignment across the two arms on whether they used social media platforms for business (column 1), whether they are currently registered on any service-oriented gig platforms at the endline (column 2); whether they received employment through any gig platform (column 3), the total number of days worked through gig platforms (column 4), and the total earnings through gig platforms (column 5) in the last 90 days – preceding the endline survey date. All the control means are measured at the endline. Equality of the VT and VTP coefficients is tested and the associated *p-values* are provided. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table 7: Impact of skilling on well-being

		Satisfaction with					
	Satisfaction index	Current level of education	Current level of skills	Work you are doing presently	Ability to contribute to household expenditure	Financial situation of your household	Life as a whole
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: ITT							
VT	-0.046	-0.094*	-0.023	-0.099**	-0.056	0.001	0.020
	(0.031)	(0.051)	(0.052)	(0.049)	(0.047)	(0.048)	(0.048)
VTP	0.056*	-0.022	0.125**	0.031	0.071	0.084*	0.052
	(0.030)	(0.051)	(0.051)	(0.048)	(0.048)	(0.049)	(0.049)
VT = VTP [p-value]	[0.000]	[0.123]	[0.001]	[0.003]	[0.002]	[0.060]	[0.468]
Panel B: 2SLS							
VT	-0.065	-0.133*	-0.032	-0.141**	-0.080	0.002	0.028
	(0.043)	(0.072)	(0.073)	(0.069)	(0.066)	(0.067)	(0.068)
VTP	0.120	-0.085	0.298**	0.041	0.154	0.206	0.132
	(0.080)	(0.133)	(0.135)	(0.127)	(0.127)	(0.129)	(0.129)
VT = VTP [p-value]	[0.003]	[0.638]	[0.001]	[0.057]	[0.013]	[0.037]	[0.283]
N	1,857	1,857	1,857	1,857	1,857	1,857	1,857

Note: Panel A shows the ITT estimates for the effect of the treatment assignment on the overall satisfaction index (column 1), which is constructed from self-reported measures for satisfaction with: current level of education (column 2), skills (column 3), present work (column 4), ability to contribute to household expenditure (column 5), financial situation of household (column 6), and life as a whole (column 7). Panel B shows the ToT estimates using 2SLS after instrumenting training completion with treatment assignment. For each *satisfaction measure*, respondents were asked to imagine a ladder with steps numbered from 1 (bottom) to 10 (top), where the top represents the best possible life and the bottom the worst. They were then asked to indicate the step they felt they personally stood on. The satisfaction index was constructed using the six sub-measures in columns (2)–(7), following Kling et al. (2007). Each sub-measure is a z-score, which is standardized using the baseline mean and standard deviation of the control group. The baseline control means for the index and its sub-measures are all zero. Equality of the VT and VTP coefficients is tested and the associated *p-values* are provided in both panels. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

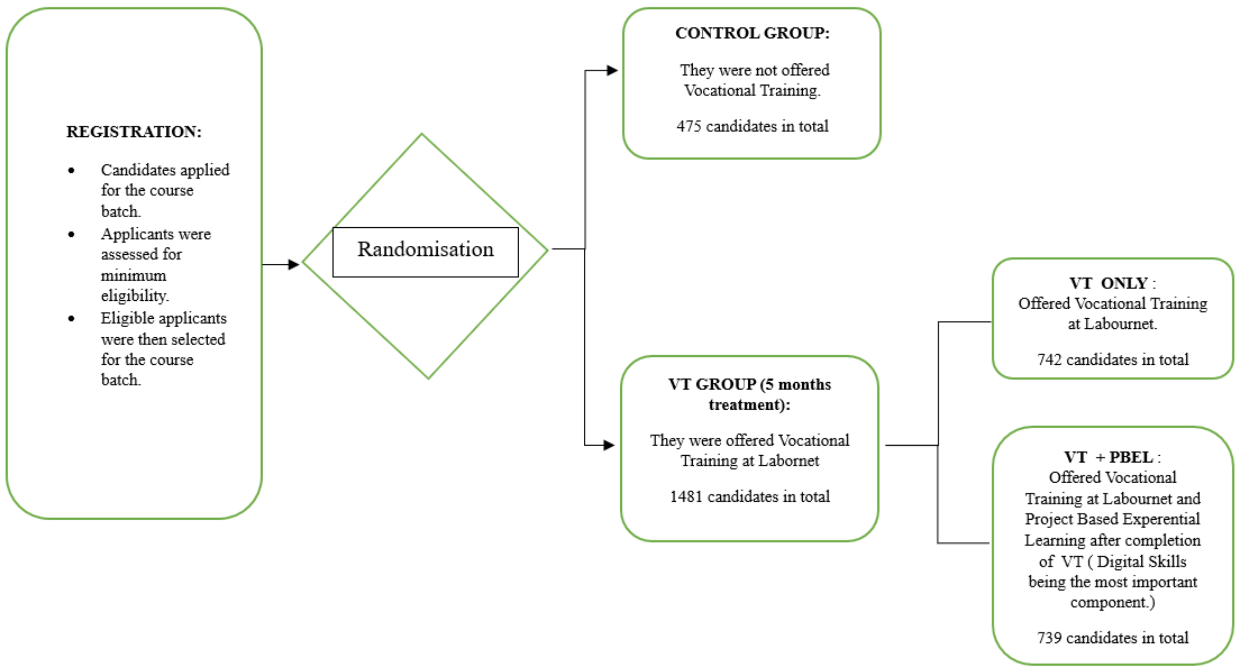
Table 8: Cost-benefit analysis of vocational-plus skilling

	Control vs VTP		
	(1)	(2)	(3)
Social discount rate = 5%			
Remaining expected productive life of beneficiaries	20 years	25 years	30 years
Panel A: Estimated cost			
Total cost per individual at year 0 [INR]:	36517	36517	36517
(i) Training cost per individual	2570	2570	2570
(ii) Foregone earnings - average at baseline (overall)	33947	33947	33947
Panel B: Estimated total benefits from non-labor market outcomes			
(i) NPV change in total satisfaction year 1 and beyond-forever (ITT)	4960	5609	6118
(ii) NPV change in total earnings year 1 and beyond-forever (ITT) (social discount rate=10%)	3388	3613	3752
Panel C: Estimated benefits from labor market			
(i) NPV change in total earnings year 1 and beyond-forever (ITT)	53388	60378	65856
(ii) NPV change in total earnings year 1 and beyond-forever (ITT) (social discount rate=10%)	36472	38886	40385
Benefit-to-cost ratio	1.60	1.81	1.97
Internal Rate of Return (IRR)	0.113	0.121	0.124

Note: The table presents the welfare calculations for Vocational Training (VT) along with the Project-based Experiential Learning (PBEL) component vs. no training in columns (1), (2), and (3) for 20 years, 25 years, and 30 years of remaining expected productive life of beneficiaries respectively. Panel A shows the total cost of training incurred per individual, Panel B takes into account non-monetary gains from satisfaction, Panel C shows the NPV of incremental earnings working in the beauty sector (preferred sector), and finally, Panel D shows sensitivity of IRR calculations to changes in foregone earnings. Foregone earnings in Panel A have been calculated as average monthly earnings across all sectors and types of work at baseline (conditional on employment in the last 90 days preceding the survey date), multiplied by 5, since trainees attended the program for approximately 5 months. The valuation method used in Panel B to estimate the monetary value from gains in satisfaction is explained in details in Appendix B. For the computation of NPV in Panel C, we used as input the gain in earnings in column (6), Panel A, Table 4, with the assumption that those who were assigned treatment would be able to move to the beauty sector (preferred sector) and work in that sector for their remaining expected productive life. All monetary values are expressed in INR.

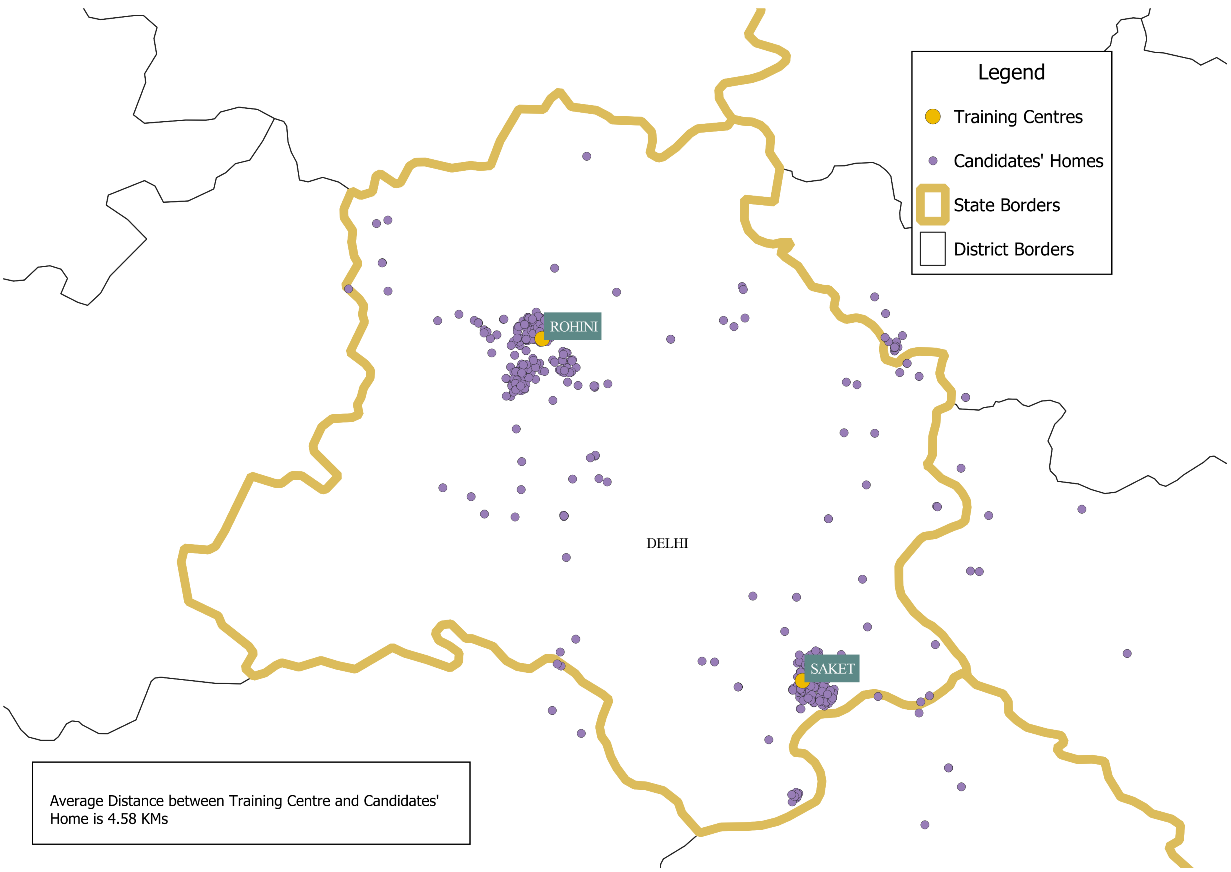
A Appendix: Additional Tables and Figures

Figure A.1: Study design



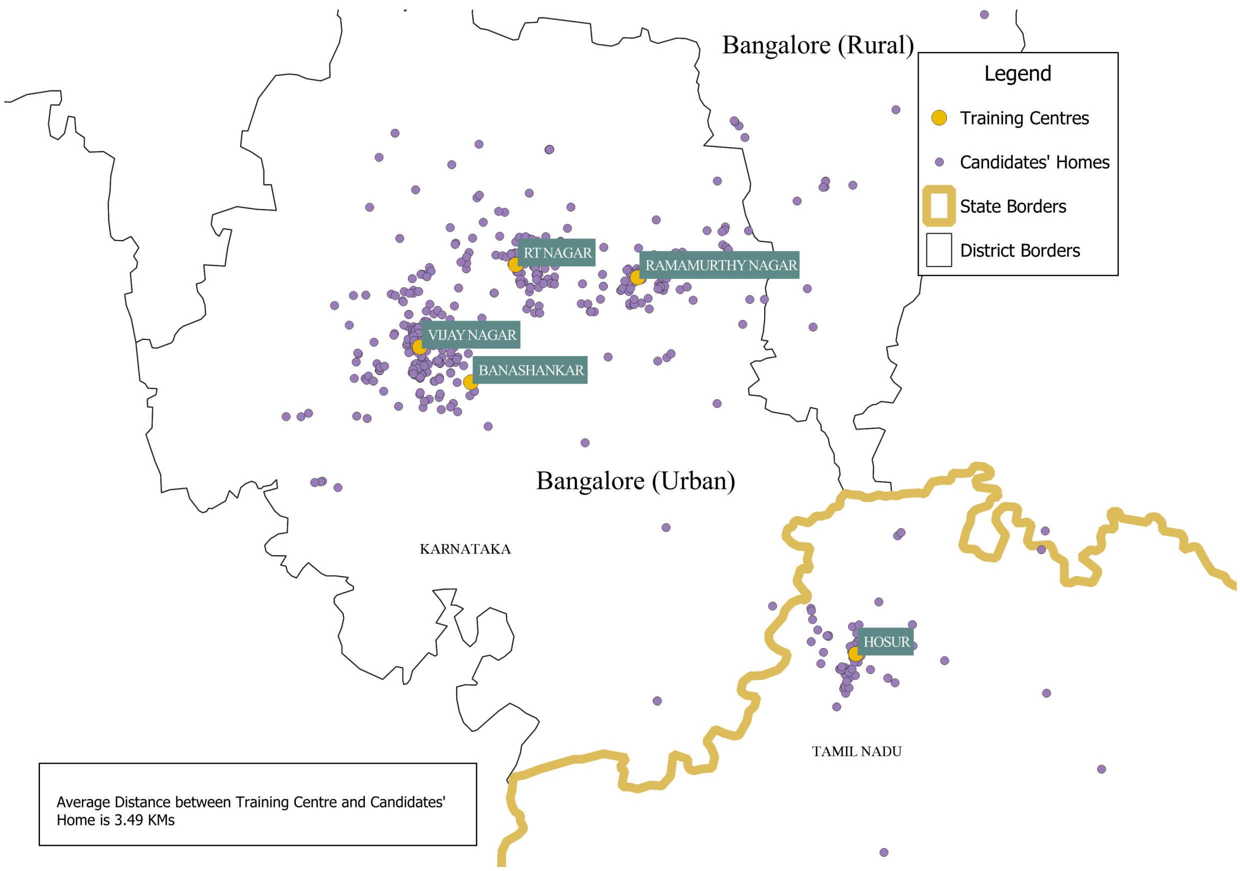
Note: The above figure illustrates our study design with a flow chart. First, the mobilized individuals applied for the course batch and were screened for minimum eligibility criteria. Then, we randomised selected individuals within a batch – each batch consisted of 40 selected candidates, out of which 10 were assigned to the control group and not offered any training, 15 were assigned to the Vocational Training or VT group, and 15 were assigned to the VTP group and offered Vocational Training along with the Project-Based Experiential Learning (PBEL) component.

Figure A.2: Training centres in Delhi



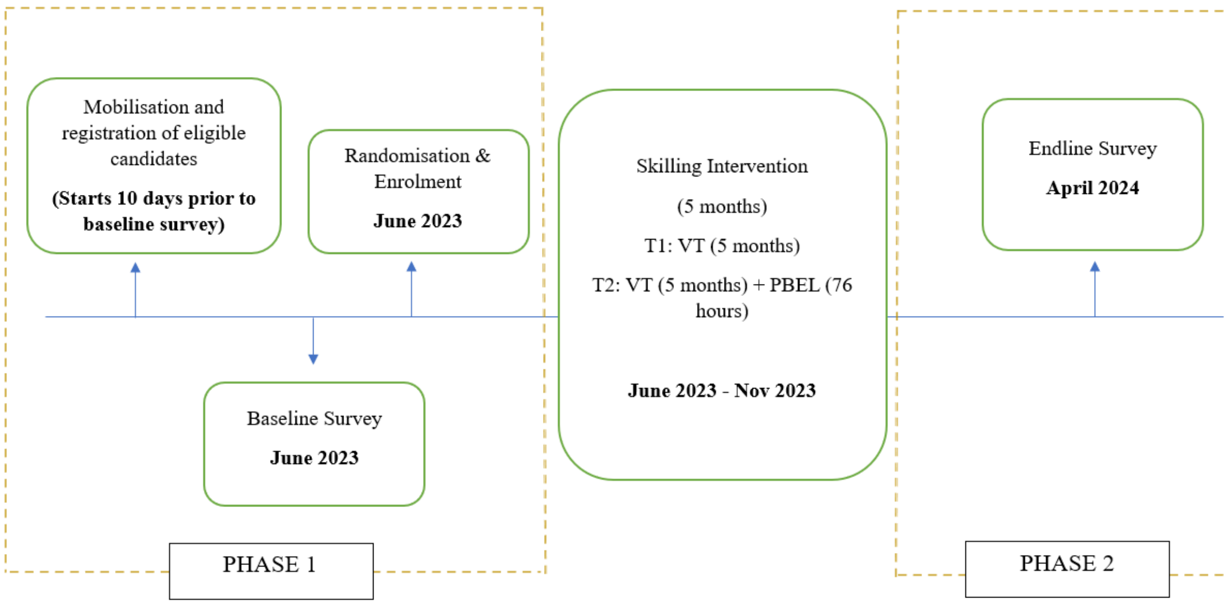
Note: The above figure maps out the Labournet training centres in Delhi along with the locations of candidates' homes, and the state and district borders. The training centres would mobilize candidates within a 5 km radius of the centres.

Figure A.3: Training centres in Bangalore



Note: The above figure maps out the Labournet training centres used to train candidates in Bangalore along with the locations of candidates' homes, and the state and district borders. The training centres would mobilize candidates within a 5 km radius of the centres.

Figure A.4: Study timeline



Note: The above figure provides an illustrative example using the training cohort that started the skilling program in June 2023. We mobilized and enrolled candidates into the skilling program in multiple batches from June 2023 - April 2024 across two training centres in Delhi and five in Bangalore. The endline survey of each batch was conducted about 10 months after the training start date of that batch.

Table A.1: Vocational training course content

Module Name	F2F (Hrs)	SL (Hrs)	Projects (Hrs)	Total (Hrs)
Panel A: Vocational Training (VT)				
Introduction to the course	1	0.03	0	1.03
Introduction to industry and job role	5	0.5	2	7.5
Health and safety at workplace	6	0.5	2	8.5
Maintaining the work area	4	0.5	2	6.5
Manicure services	8	1	2	11
Pedicure services	8	1	2	11
Depilation services - bleaching	4	0.03	0	4.03
Depilation services - threading	12	1	2	15
Depilation services - waxing	8	1	2	11
Skin anatomy	4	1	0	5
Basic skin care treatments	8	1	0	9
Skin care treatments - facials	12	1	2	15
Body massage services	12	1	2	15
Basic hair care treatments	12	0.03	0	12.03
Introduction to hair styling	8	0.5	0	8.5
Simple mehendi designs	8	0.5	2	10.5
Basic saree draping	8	0.5	2	10.5
Basic makeup services - products and tools	4	0.5	2	6.5
Basic makeup services - client prep	4	0.25	0	4.25
Basic makeup services - application	8	0.5	2	10.5
Basic makeup services - clean up and aftercare	4	0.25	0	4.25
Reflection, feedback and learning	2	0	0	2
Total	150	13	26	189
Panel B: Project-based Experiential Learning (PBEL)				
Digital Skills for Lifelong Learning	2	0.5	2	4.5
Being Digitally Smart - Know your Phone	4	0.5	2	6.5
Being Digitally Smart - Social Media Presence	4	0.5	2	6.5
Digital Safety	2	0.5	0	2.5
Portfolio Building for Digilocker	8	0	0	8
Communication Skills	6	0.5	2	8.5
Body Language	2	0.5	2	4.5
Customer Service	6	0.5	2	8.5
Professional Behaviour and Conduct	4	0.5	2	6.5
Work Ethics	2	0.5	2	4.5
Time Management	2	0.5	2	4.5
Personal Finance - Savings and Budgets	4	0.5	2	6.5
Personal Grooming and Hygiene	2	0.5	2	4.5
Total	48	6	22	76

Note: F2F: Face to Face, SL: Self-learning. This table presents the breakdown of the number of hours assigned to each module taught in the Vocational Training component in Panel A, and in the Project-based Experiential Learning component in Panel B. The training utilised various methods of teaching including Face to Face classes, self-learning, and projects.

Table A.2: Schedule of vocational training batches

	Bangalore (1)	Delhi (2)	All (3)
Jun 2023	6	0	6
Jul 2023	0	2	2
Aug 2023	3	3	6
Sep 2023	3	3	6
Oct 2023	5	4	9
Nov 2023	2	2	4
Dec 2023	6	2	8
Jan 2024	4	1	5
Feb 2024	5	1	6
Mar 2024	2	1	3
Apr 2024	2	0	2
Total	38	19	57

Note: This table shows the number of batches formed at the training centres in Bangalore (column 1), Delhi (column 2), and across both the cities (column 3) in each month for the duration of the intervention.

Table A.3: Definition of household and individual covariates

Household characteristics	
Hindu	= 1 if head of household is Hindu; 0, otherwise.
ST and SC	= 1 if head of household is Scheduled Tribe (ST) or Scheduled Caste (SC); 0, otherwise.
OBC	= 1 if head of household is Other Backward Caste (OBC); 0, otherwise.
HH head: Female	= 1 if the head of the household is female; 0, otherwise.
HH head: High school education	= 1 if the highest educational qualification of the head of the household is high school education or diploma/certificate course (high school); 0, otherwise.
HH head: College & above education	= 1 if the highest educational qualification of the head of the household is college or graduate school or diploma/certificate course (college & above); 0, otherwise.
Number of under-5 children in HH	= Number of children, aged less than 5-years-old, in respondent's household.
Asset index	= Index of household assets created using principal components analysis - asset list includes house ownership, a list of consumer durables, and agricultural land ownership.
Individual characteristics	
Age	= Respondent's age in years.
High school education	= 1 if respondent's highest educational qualification is high school education or diploma/certificate course (high school); 0, otherwise.
College & above education	= 1 if respondent's highest educational qualification is college or graduate school or diploma/certificate course (college & above); 0, otherwise.
Currently married	= 1 if respondent is married.
Mobile phone/internet usage intensity	= Average number of hours respondent uses mobile phone/internet for in a typical day.
Previous skilling	= 1 if respondent has completed any formal or informal skill training (excluding any on-going) at the time of the survey; 0, otherwise.

Note: This table provides detailed definitions of variables used for baseline controls in all of our specifications. All these variables were measured at the time of the baseline survey.

Table A.4: Household and individual characteristics by state (at baseline)

Variable	Mean		
	All (1)	Delhi (2)	Bangalore (3)
Household characteristics			
Hindu	0.870 (0.337)	0.858 (0.350)	0.876 (0.330)
ST or SC	0.308 (0.462)	0.293 (0.456)	0.316 (0.465)
OBC	0.472 (0.499)	0.324 (0.468)	0.553 (0.497)
HH head: Female	0.148 (0.355)	0.109 (0.312)	0.170 (0.376)
HH head: High school education	0.155 (0.362)	0.155 (0.362)	0.155 (0.362)
HH head: College & above education	0.141 (0.348)	0.097 (0.297)	0.164 (0.371)
Number of under-5 children in HH	0.258 (0.517)	0.244 (0.541)	0.265 (0.503)
Asset index	0.000 (1.487)	0.323 (1.676)	-0.176 (1.342)
Individual characteristics			
Age	24.344 (6.062)	21.848 (4.882)	25.701 (6.210)
High school education	0.458 (0.498)	0.498 (0.500)	0.436 (0.496)
College & above education	0.209 (0.406)	0.184 (0.388)	0.222 (0.416)
Currently married	0.427 (0.495)	0.192 (0.394)	0.555 (0.497)
Mobile phone/internet usage intensity (hours in a typical day)	3.051 (1.746)	3.160 (1.853)	2.991 (1.682)
Previous skilling	0.085 (0.280)	0.093 (0.290)	0.081 (0.273)
Current employment	0.165 (0.371)	0.067 (0.250)	0.218 (0.413)
Days worked (90 days)	9.354 (21.436)	3.869 (14.913)	12.337 (23.737)
Earnings (Rs.) (90 days)	3784.758 (10956.109)	1367.658 (7672.537)	5099.187 (12184.584)
N	1956	689	1267

Note: SC: Scheduled Caste, ST: Scheduled Tribes, OBC: Other Backward Classes, HH: household. This table presents the average baseline household and individual characteristics for the full sample (column 1), Delhi (column 2), and Bangalore (column 3). Means are reported with standard deviation (SD) in parentheses. The number of respondents in the full sample and each city is reported in the last row. We measure current employment at the time of the survey. Days worked and earnings are the total days the respondent has worked for and her total earnings in the last 90 days preceding the baseline survey date. They are unconditional on employment, i.e., for our calculation, we take the value of 0 for days worked and earnings for those who were unemployed in the last 90 days preceding the baseline survey. Appendix Table A.3 provides detailed definitions for the other variables.

Table A.5: Household and individual characteristics vs. Periodic Labor Force Survey (PLFS)

	PLFS 2023-24 (1)	Baseline (2)
Household characteristics		
Hindu	0.818	0.870
	(0.386)	(0.337)
ST or SC	0.228	0.308
	(0.420)	(0.462)
OBC	0.440	0.472
	(0.497)	(0.499)
HH head: Female	0.173	0.148
	(0.378)	(0.355)
HH head: High school education	0.169	0.155
	(0.375)	(0.362)
HH head: College & above education	0.211	0.141
	(0.408)	(0.348)
Individual characteristics		
Age	26.477	24.344
	(5.210)	(6.062)
High school education	0.278	0.458
	(0.448)	(0.498)
College & above education	0.337	0.209
	(0.473)	(0.406)
Currently married	0.608	0.427
	(0.488)	(0.495)
Current employment	0.245	0.165
	(0.430)	(0.371)
Days worked (90 days)	18.170	9.354
	(32.522)	(21.436)
Earnings (Rs.) (90 days)	13534.000	3784.758
	(35451.635)	(10956.109)
N	1690	1956

Note: SC: Scheduled Caste, ST: Scheduled Tribes, OBC: Other Backward Classes, HH: household. This table presents the average household and individual characteristics for two samples: (a) women aged 18-35 residing in the states of Delhi and Karnataka and interviewed in PLFS 2023-24 (column 1) and (b) women in our baseline sample (column 2). Means are reported with standard deviations (SD) in parentheses. We measure current employment at the time of the survey. Days worked and earnings are the total days the respondent has worked for and her total earnings in the last 90 days preceding the baseline survey date. They are unconditional on employment, i.e., for our calculation, we take the value of 0 for days worked and earnings for those who were unemployed in the last 90 days preceding the baseline survey. Appendix Table A.3 provides detailed definitions for the other variables.

Table A.6: Probability of training completion: by distance from training centres

	(1)	(2)
Less than 5km	0.090**	0.075*
	(0.039)	(0.040)
VTP	-0.027	-0.034
	(0.050)	(0.049)
VTP $\times$ Less than 5km	-0.000	-0.000
	(0.056)	(0.054)
N	1,405	1,405

Note: This table presents the differential impact of assigned treatment arm on the probability of completing the VT component for women who were randomly assigned to vocational treatment, by the distance between the residential location and the closest training centre. The distance was calculated as the length (in km) of the shortest path between the women's homes and the training centres. The interaction term captures differential effects on women assigned VTP who reside within 5kms from their training centres. The first row captures effect on women assigned VT, residing within 5kms from their training centres. Column (1) specification does not include centre and quarter fixed effects and column (2) includes both the centre and quarter fixed effects. Both specifications include controls for baseline characteristics. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.7: Attrition analysis

	(1)	(2)	(3) Heterogeneous
VT	0.004	0.004	-0.054
	(0.013)	(0.013)	(0.085)
VTP	0.004	0.005	-0.106
	(0.013)	(0.013)	(0.080)
Asset index		0.003	0.009
		(0.003)	(0.007)
ST or SC		-0.019	-0.007
		(0.015)	(0.027)
OBC		-0.027*	-0.028
		(0.014)	(0.025)
Hindu		-0.018	-0.046
		(0.018)	(0.039)
HH head: Female		-0.006	0.020
		(0.015)	(0.033)
HH head: High school education		0.020	0.007
		(0.016)	(0.027)
HH head: College & above education		-0.007	-0.000
		(0.015)	(0.029)
Number of under-5 children in HH		0.007	0.012
		(0.009)	(0.019)
Currently married		-0.049***	-0.057*
		(0.018)	(0.030)
High school education		-0.013	0.009
		(0.011)	(0.020)
College & above education		-0.000	0.010
		(0.015)	(0.027)
Age		0.001	0.001
		(0.001)	(0.002)
Mobile phone/internet usage intensity		-0.001	-0.012***
		(0.003)	(0.004)
Previous skilling		-0.009	-0.049*
		(0.018)	(0.028)
N	1,956	1,956	1,956
F statistic on interactions	.	.	1.144
p-value	.	.	[0.240]

Note: SC: Scheduled Caste, ST: Scheduled Tribes, OBC: Other Backward Classes, HH: household. The table shows the probability of attrition at the endline based on treatment assignment without controlling for any household/individual characteristics at baseline in column 1. Column 2 controls for baseline household and individual characteristics, and Column 3 additionally interacts the baseline characteristics with the treatment assignment to test whether there is a differential effect of baseline characteristics by treatment assignment. Centre and quarter fixed effects are included in all the specifications. Appendix table A.3 provides detailed variable definitions. The 'F statistic on interactions' shows the F-stat from the test for the joint significance of the characteristics interacted with the treatment assignment - the *p-value* associated with the test is reported in the last row. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.8: First stage: Current employment status (extensive margin)

	Current employment							
	Sector				Type			
	Any		Beauty		Self-employed		Salaried	
	VT completion	VTP completion	VT completion	VTP completion	VT completion	VTP completion	VT completion	VTP completion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VT	0.705***	0.001	0.706***	0.001	0.706***	0.001	0.705***	0.002
	(0.020)	(0.003)	(0.020)	(0.003)	(0.020)	(0.003)	(0.020)	(0.003)
VTP	-0.099***	0.411***	-0.099***	0.410***	-0.098***	0.411***	-0.099***	0.411***
	(0.014)	(0.019)	(0.014)	(0.019)	(0.014)	(0.019)	(0.014)	(0.019)
SW F-stat	1191	1232	1198	1235	1194	1235	1192	1232
N	1,857	1,857	1,857	1,857	1,857	1,857	1,857	1,857

Note: This table presents the first-stage estimates from the 2SLS regressions corresponding to Table 3, where treatment assignment to VT and VTP is used as instruments for VT and VTP completion. Sanderson-Windmeijer (SW) first-stage F statistics are reported for tests of weak identification of endogenous regressors – training completion of VT and VTP, which we have instrumented with treatment assignment to VT and VTP, respectively. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.9: Decomposition of labor market impact: Days worked and earnings (VTP)

	Days worked				Earnings			
	Sector		Type		Sector		Type	
	Any	Beauty	Self-employed	Salaried	Any	Beauty	Self-employed	Salaried
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total effect	3.195	2.335	2.249	1.315	836.818	1,070.997	304.782	508.222
	(1.714)	(1.003)	(0.955)	(1.570)	(1014.263)	(569.630)	(625.442)	(836.066)
	[0.062]	[0.020]	[0.019]	[0.402]	[0.409]	[0.060]	[0.626]	[0.543]
Extensive margin	1.366	2.029	1.884	-0.175	706.655	1,079.367	1,103.494	-86.632
	(1.526)	(0.835)	(0.832)	(1.444)	(789.807)	(444.347)	(487.017)	(714.734)
	[0.371]	[0.015]	[0.023]	[0.904]	[0.371]	[0.015]	[0.023]	[0.904]
Intensive margin	1.829	0.306	0.364	1.490	130.162	-8.370	-798.712	594.854
	(0.910)	(0.546)	(0.551)	(0.705)	(762.424)	(424.257)	(523.171)	(527.550)
	[0.044]	[0.576]	[0.508]	[0.034]	[0.864]	[0.984]	[0.127]	[0.259]
Treatment effect conditional on employment	5.054	2.427	2.660	6.367	359.564	-66.425	-5830.014	2,542.111
	(2.514)	(4.337)	(4.021)	(3.011)	(2106.143)	(3367.116)	(3818.764)	(2254.486)
	[0.044]	[0.576]	[0.508]	[0.034]	[0.864]	[0.984]	[0.127]	[0.259]
Baseline VTP Mean	9.75	1.11	3.54	6.14	3,828.98	625.63	1,534.50	2,254.59

Note: This table shows decompositions of treatment effects for VTP arm on a given job characteristic in the column into extensive and intensive margin effects. The extensive margin effect is obtained by multiplying the treatment effect on the job characteristic by average of that characteristic in control group who are employed (either overall or in that work type). The intensive margin effect is the difference between the total treatment effect on a given job characteristic and the extensive margin effect on the characteristic. This captures the treatment effect on the characteristic which is due to changes in the characteristic for the employed candidates (either overall or in that work type) in the treatment group. Lastly, the conditional effect is the implied mean change in the characteristic per employed (either overall or in that work type) treatment group candidate. VTP group employment rate in the last 90 days (preceding the endline survey date) is 36% and hence the intensive margin effects is roughly 36% of the conditional effect in column (1). Proportion of women employed in the beauty sector in the same 90 days in VTP arm is 13% and the intensive margin effects is roughly 13% of the conditional effect in column (2). Similarly, the intensive margin effects are scaled by employment rates in the VTP arm for the type of work mentioned in each column. Robust standard errors in parentheses and associated *p-values* are in brackets.

Table A.10: Impact of skilling on hourly wage rate

	Hourly wage			
	Sector		Type	
	Any	Beauty	Self-employed	Salaried
	(1)	(2)	(3)	(4)
Panel A: VT				
Total effect	-1.940	4.034	1.132	-2.712
	(3.973)	(3.040)	(3.569)	(2.963)
	[0.625]	[0.185]	[0.751]	[0.360]
Extensive margin	-3.690	0.679	0.809	-2.965
	(2.290)	(1.658)	(2.241)	(1.789)
	[0.107]	[0.682]	[0.718]	[0.097]
Intensive margin	1.750	3.356	0.324	0.253
	(3.213)	(2.357)	(2.769)	(2.345)
	[0.586]	[0.155]	[0.907]	[0.914]
Treatment effect conditional	5.952	36.475	3.301	1.267
on employment	(10.930)	(25.621)	(28.260)	(11.724)
	[0.586]	[0.155]	[0.907]	[0.914]
Panel B: VTP				
Total effect	5.507	10.629	9.596	-2.418
	(3.975)	(3.582)	(4.107)	(2.286)
	[0.166]	[0.003]	[0.020]	[0.290]
Extensive margin	2.288	3.862	5.727	-0.254
	(2.336)	(1.764)	(2.390)	(1.828)
	[0.327]	[0.029]	[0.017]	[0.889]
Intensive margin	3.218	6.767	3.869	-2.164
	(3.163)	(2.879)	(3.228)	(1.484)
	[0.309]	[0.019]	[0.231]	[0.145]
Treatment effect conditional	8.891	53.708	28.240	-9.249
on employment	(8.738)	(22.852)	(23.561)	(6.341)
	[0.309]	[0.019]	[0.231]	[0.145]
Baseline VTP Mean	16.77	2.53	8.65	7.25

Note: This table shows decomposition of treatment effects on hourly wage rate across all types of work (column 1), beauty sector work (column 2), self-employed work (column 3) and regular/salaried work (column 4) into extensive and intensive margin effects for VT and VTP arms in Panels A and B, respectively. The extensive margin effect is obtained by multiplying the treatment effect on the hourly wage rate (within a column) by average of that hourly wage in control group who are employed (in that work type). The intensive margin effect is the difference between the total treatment effect on hourly wage and the extensive margin effect on hourly wage. This captures the treatment effect on hourly wage which is due to changes in the hourly wage for the employed candidates (in that work type) in the treatment group. Lastly, the conditional effect is the implied mean change in the hourly wage per employed (in that work type) treatment group candidate. VTP group average employment rate in the last 90 days (preceding the endline survey date) is 36% and hence the intensive margin effects is roughly 36% of the conditional effect in column (1), Panel B. Similarly, the intensive margin effects are scaled by average employment rates for the type of work in each column for VT arm in Panel A and VTP arm in Panel B. Robust standard errors in parentheses and associated p-values are in brackets.

Table A.11: Impact of skilling on job attributes

	Hours per working day	Outside home workplace	Time taken to travel to & from workplace	Social security	Healthcare benefit	Paid leaves
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: VT						
Total effect	-0.315	-0.028	-0.016	0.006	0.009	0.003
	(0.193)	(0.024)	(1.394)	(0.012)	(0.008)	(0.007)
	[0.103]	[0.243]	[0.991]	[0.617]	[0.261]	[0.668]
Extensive margin	-0.219	-0.024	-0.947	-0.004	-0.001	-0.001
	(0.180)	(0.020)	(0.776)	(0.003)	(0.001)	(0.001)
	[0.222]	[0.222]	[0.222]	[0.222]	[0.222]	[0.222]
Intensive margin	-0.095	-0.004	0.931	0.010	0.010	0.004
	(0.079)	(0.014)	(1.104)	(0.012)	(0.007)	(0.007)
	[0.230]	[0.789]	[0.399]	[0.391]	[0.184]	[0.548]
Treatment effect conditional	-0.324	-0.012	3.167	0.034	0.033	0.015
on employment	(0.270)	(0.046)	(3.754)	(0.040)	(0.025)	(0.024)
	[0.230]	[0.789]	[0.399]	[0.391]	[0.184]	[0.548]
Panel B: VTP						
Total effect	0.020	0.006	0.597	0.008	0.005	-0.003
	(0.198)	(0.024)	(1.391)	(0.012)	(0.007)	(0.007)
	[0.920]	[0.803]	[0.668]	[0.505]	[0.475]	[0.668]
Extensive margin	0.165	0.018	0.713	0.003	0.001	0.001
	(0.185)	(0.020)	(0.796)	(0.003)	(0.001)	(0.001)
	[0.371]	[0.371]	[0.371]	[0.371]	[0.371]	[0.371]
Intensive margin	-0.145	-0.013	-0.116	0.005	0.005	-0.004
	(0.084)	(0.014)	(1.122)	(0.012)	(0.007)	(0.007)
	[0.083]	[0.375]	[0.918]	[0.639]	[0.533]	[0.569]
Treatment effect conditional	-0.400	-0.035	-0.320	0.015	0.013	-0.011
on employment	(0.231)	(0.039)	(3.098)	(0.032)	(0.020)	(0.019)
	[0.083]	[0.375]	[0.918]	[0.639]	[0.533]	[0.569]
Baseline VTP Mean	1.08	0.13	3.80	0.02	0.01	0.01

Note: This table shows decomposition of treatment effects on hours worked per day (column 1), place of work being outside home (column 2), time taken to travel to & from work (in minutes) (column 3), social security (column 4), healthcare (column 5), and paid leave (column 6) provision at work into extensive and intensive margin effects for VT and VTP arms in Panels A and B, respectively. The extensive margin effect is obtained by multiplying the treatment effect on a given job attribute by average of that attribute in control group who are employed. The intensive margin effect is the difference between the total treatment effect on the job attribute and the extensive margin effect on the attribute. This captures the treatment effect on the job attribute which is due to changes in the attribute for the employed candidates in the treatment group. Lastly, the conditional effect is the implied mean change in the job attribute per employed treatment group candidate. For instance, VTP group average employment rate in the last 90 days (preceding the endline survey date) is 36% and hence the intensive margin effects is roughly 36% of the conditional across all columns in panel B. Similarly, the intensive margin effects are scaled by average of employment rate for VT arm in Panel A. Robust standard errors in parentheses and associated p-values are in brackets.

Table A.12: Heterogeneity: Impact of skilling on labor market outcomes (extensive margin)

	Current employment			
	Sector		Type	
	Any	Beauty	Self-employed	Salaried
	(1)	(2)	(3)	(4)
Panel A: Household Wealth				
VT	-0.018	0.001	0.046**	-0.044
	(0.036)	(0.022)	(0.023)	(0.034)
VT × Above median	-0.014	0.013	-0.068**	0.045
	(0.050)	(0.031)	(0.032)	(0.045)
VTP	0.022	0.043*	0.048**	-0.014
	(0.036)	(0.023)	(0.023)	(0.033)
VTP × Above median	0.016	-0.014	-0.019	0.037
	(0.052)	(0.033)	(0.034)	(0.046)
Panel B: Distance to Nearest Bus Stop				
VT	-0.003	0.021	0.023	-0.008
	(0.031)	(0.020)	(0.019)	(0.028)
VT × More than 0.5km	-0.066	-0.042	-0.038	-0.039
	(0.053)	(0.032)	(0.034)	(0.048)
VTP	0.083***	0.050**	0.059***	0.037
	(0.032)	(0.020)	(0.021)	(0.028)
VTP × More than 0.5km	-0.163***	-0.043	-0.066*	-0.103**
	(0.053)	(0.035)	(0.035)	(0.048)
N	1,857	1,857	1,857	1,857

Notes: Panel A shows the differential ITT estimates of the impact of assigned treatment arms on whether the individual was employed in any sector (column 1), in the beauty sector (column 2), in self-employed work (column 3), and regular/salaried work (column 4), by the median cut of household wealth. Panel B shows the differential ITT estimates of the impact of assigned treatment arms on the same outcomes, by respondents' distance to the nearest bus-stop. Interaction terms in Panel A capture differential effects on women who belong to households with higher (above median) wealth and interaction terms in Panel B capture differential effects on women who reside in areas with the nearest bus-stop more than half a km away. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.13: Heterogeneity: Impact of skilling on labor market outcomes in beauty & wellness sector

	Beauty sector					
	Current employment		Days worked		Earnings	
	Self-employed	Salaried	Self-employed	Salaried	Self-employed	Salaried
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Household Wealth						
VT	0.040***	-0.041**	0.985*	-1.465	692.000	-590.394
	(0.015)	(0.017)	(0.557)	(1.103)	(463.126)	(449.453)
VT × Above median	-0.048**	0.055**	-1.396	2.328	-1062.832	689.521
	(0.024)	(0.023)	(0.936)	(1.587)	(815.717)	(641.477)
VTP	0.060***	-0.021	2.139***	0.043	804.387*	-38.965
	(0.016)	(0.018)	(0.713)	(1.189)	(478.426)	(492.648)
VTP × Above median	-0.050**	0.036	-1.449	1.421	-107.113	555.713
	(0.025)	(0.025)	(1.143)	(1.739)	(906.938)	(757.798)
Panel B: Distance to Nearest Bus Stop						
VT	0.031**	-0.016	0.738	-0.559	312.863	-426.549
	(0.015)	(0.014)	(0.571)	(1.031)	(549.241)	(410.100)
VT × More than 0.5km	-0.048**	0.010	-1.429	0.753	-540.621	544.274
	(0.024)	(0.024)	(0.931)	(1.506)	(621.574)	(631.353)
VTP	0.058***	-0.013	2.139***	-0.092	1136.202*	-134.254
	(0.016)	(0.015)	(0.706)	(1.072)	(598.802)	(468.425)
VTP × More than 0.5km	-0.069***	0.029	-2.224*	2.487	-1242.175*	1113.389
	(0.024)	(0.027)	(1.145)	(1.780)	(730.720)	(826.981)
N	1,857	1,857	1,857	1,857	1,857	1,857

Notes: Panel A shows the differential ITT estimates of the impact of assigned treatment arms on whether the individual was employed in the beauty sector in self-employed work (column 1), and regular/salaried work (column 2) - at the endline; the total number of days worked in the beauty sector in self-employed work (column 3), and regular/salaried work (column 4) in the last 90 days (preceding the endline survey date); the total earnings in the beauty sector in self-employed work (column 5), and regular/salaried work (column 6) in the last 90 days (preceding the endline survey date), by the median cut of household wealth. Panel B shows the differential ITT estimates of the impact of assigned treatment arms on the same outcomes, by respondents' distance to the nearest bus-stop. Interaction terms in Panel A capture differential effects on women who belong to households with higher (above median) wealth and interaction terms in Panel B capture differential effects on women who reside in areas with the nearest bus-stop more than half a km away. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.14: Robustness: Impact of skilling on labor market outcomes (extensive margin)

	Current employment			
	Sector		Type	
	Any	Beauty	Self-employed	Salaried
	(1)	(2)	(3)	(4)
Panel A: PDS Lasso				
VT	-0.023	0.007	0.012	-0.020
	(0.025)	(0.017)	(0.017)	(0.022)
VTP	0.027	0.036**	0.038**	0.001
	(0.025)	(0.017)	(0.017)	(0.022)
VT = VTP [p-value]	[0.027]	[0.051]	[0.090]	[0.289]
Panel B: FDR q-val				
VT	-0.025	0.007	0.011	-0.021
	(0.025)	(0.016)	(0.016)	(0.023)
	{0.648}	{0.648}	{0.648}	{0.648}
VTP	0.029	0.036**	0.038**	0.004
	(0.026)	(0.017)	(0.017)	(0.023)
	{0.338}	{0.061}	{0.061}	{0.878}
VT = VTP [p-value]	[0.015]	[0.056]	[0.081]	[0.204]
Panel C: Inverse-Probability Weighting (IPW)				
VT	-0.024	0.008	0.011	-0.021
	(0.025)	(0.016)	(0.016)	(0.023)
VTP	0.029	0.036**	0.038**	0.004
	(0.026)	(0.017)	(0.017)	(0.023)
VT = VTP [p-value]	[0.016]	[0.062]	[0.083]	[0.200]
N	1,857	1,857	1,857	1,857
Panel D: Alternative definition of completion of VTP (ToT)				
VT	-0.035	0.010	0.016	-0.030
	(0.035)	(0.022)	(0.022)	(0.032)
VTP	0.082	0.117**	0.125**	0.002
	(0.088)	(0.056)	(0.058)	(0.078)
VT = VTP [p-value]	[0.088]	[0.018]	[0.020]	[0.599]
N	1,857	1,857	1,857	1,857

Note: This table shows the ITT estimates for the effect of the treatment assignment on whether an individual was currently employed (column 1), currently employed in the beauty sector (column 2), currently doing self-employed work (column 3), or regular/salaried work (column 4) at the endline in Panel A, B, and C, and ToT estimates using 2SLS after instrumenting training completion with treatment assignment in Panel D. Panel A shows the estimates after using the Post-Double Selection Lasso (PDS Lasso) method of Belloni et al. (2014) to select the control variables, Panel B shows the FDR q-values (in braces) associated with the ITT estimates for the effect of the treatment assignment, Panel C shows the inverse probability weighting (IPW) estimates for the effect of the treatment assignment, and Panel D shows the ToT estimates using 2SLS after instrumenting training completion with treatment assignment on the same outcomes, using an alternative definition of VTP training completion where VTP training completion is defined as completion of both the VT and PBEL components. Equality of the VT and VTP coefficients is tested and the associated *p-values* are provided. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.15: Robustness: Impact of skilling on labor market outcomes in beauty & wellness sector

	Beauty sector					
	Current employment		Days worked		Earnings	
	Self-employed	Salaried	Self-employed	Salaried	Self-employed	Salaried
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: PDS Lasso						
VT	0.016	-0.015	0.332	-0.486	197.544	-482.969
	(0.013)	(0.012)	(0.585)	(0.858)	(453.098)	(376.196)
VTP	0.034***	-0.002	1.400**	0.813	730.919	170.400
	(0.013)	(0.012)	(0.586)	(0.859)	(453.671)	(376.650)
VT = VTP [p-value]	[0.111]	[0.216]	[0.039]	[0.088]	[0.184]	[0.050]
Panel B: FDR q-val						
VT	0.015	-0.013	0.276	-0.281	149.321	-240.192
	(0.012)	(0.012)	(0.464)	(0.778)	(396.864)	(307.323)
	{0.719}	{0.719}	{0.719}	{0.719}	{0.719}	{0.719}
VTP	0.035***	-0.003	1.421**	0.756	748.244*	238.945
	(0.012)	(0.012)	(0.558)	(0.864)	(431.996)	(389.906)
	{0.026}	{0.804}	{0.033}	{0.572}	{0.167}	{0.649}
VT = VTP [p-value]	[0.095]	[0.324]	[0.041]	[0.168]	[0.161]	[0.122]
Panel C: Inverse-Probability Weighting (IPW)						
VT	0.015	-0.013	0.289	-0.442	135.304	-313.048
	(0.012)	(0.011)	(0.466)	(0.757)	(403.689)	(294.229)
VTP	0.035***	-0.003	1.418**	0.689	744.626*	236.845
	(0.012)	(0.012)	(0.558)	(0.846)	(435.000)	(372.974)
VT = VTP [p-value]	[0.095]	[0.293]	[0.045]	[0.122]	[0.160]	[0.073]
N	1,857	1,842	1,857	1,840	1,857	1,840
Panel D: Alternative definition of completion of VTP (ToT)						
VT	0.021	-0.019	0.384	-0.402	207.167	-341.892
	(0.017)	(0.016)	(0.650)	(1.091)	(556.450)	(430.796)
VTP	0.118***	-0.016	4.603**	2.261	2423.200*	646.742
	(0.042)	(0.042)	(1.854)	(2.911)	(1451.523)	(1307.826)
VT = VTP [p-value]	[0.006]	[0.927]	[0.010]	[0.256]	[0.072]	[0.351]
N	1,857	1,857	1,857	1,857	1,857	1,857

Note: This table shows the ITT estimates for the effect of the treatment assignment on whether the individual was employed in the beauty sector in self-employed work (column 1), in regular/salaried work (column 2) at the endline; the total number of days worked in the last 90 days (preceding the endline survey date) in the beauty sector in self-employed work (column 3), in regular/salaried work (column 4); the total earnings in the last 90 days (preceding the endline survey date) in the beauty sector in self-employed work (column 5), in regular/salaried work (column 6) in Panel A, B, and C, and ToT estimates using 2SLS after instrumenting training completion with treatment assignment in Panel D. Panel A shows the estimates after using the Post-Double Selection Lasso (PDS Lasso) method of Belloni et al. (2014) to select the control variables, Panel B shows the FDR q-values (in braces) associated with the ITT estimates for the effect of the treatment assignment, Panel C shows the inverse probability weighting (IPW) estimates for the effect of the treatment assignment, and Panel D shows the ToT estimates using 2SLS after instrumenting training completion with treatment assignment on the same outcomes, using an alternative definition of VTP training completion where VTP training completion is defined as completion of both the VT and PBEL components. Equality of the VT and VTP coefficients is tested and the associated *p-values* are provided. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.16: Impact of skilling on labor market outcomes (extensive margin): by density of trainees

	Current employment			
	Sector		Type	
	Any	Beauty	Self-employed	Salaried
	(1)	(2)	(3)	(4)
VT	-0.020	0.014	0.014	-0.020
	(0.038)	(0.024)	(0.024)	(0.034)
Above median	0.026	-0.024	-0.017	0.037
	(0.050)	(0.031)	(0.033)	(0.044)
VT × Above median	-0.008	-0.014	-0.005	-0.001
	(0.051)	(0.031)	(0.032)	(0.045)
VTP	0.090**	0.063**	0.040	0.056
	(0.040)	(0.026)	(0.025)	(0.035)
VTP × Above median	-0.120**	-0.053	-0.004	-0.103**
	(0.052)	(0.033)	(0.035)	(0.045)
N	1,857	1,857	1,857	1,857

Notes: This table presents the differential ITT estimates of the impact of assigned treatment arms on whether the individual was employed in any sector (column 1), in beauty sector (column 2), in self-employed work (column 3), and regular/salaried work (column 4) – at endline, by median cut of the number of treated individuals who were assigned their treatment group in the same month within a radius of 2km. Interaction terms capture differential effects on women who have higher (above median) number of treated individuals in their assigned treatment group in the same month within a radius of 2km. All specifications include baseline characteristics, training centre FE and quarter FE. The specifications also control for the number of registered women in the 2km radius of a woman's home in her training batch. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.17: Impact of skilling on labor market outcomes in the beauty & wellness sector: by density of trainees

	Beauty sector					
	Current employment		Days worked		Earnings	
	Self-employed	Salaried	Self-employed	Salaried	Self-employed	Salaried
	(1)	(2)	(3)	(4)	(5)	(6)
VT	0.012	-0.006	0.319	0.123	83.847	-420.905
	(0.018)	(0.018)	(0.709)	(1.306)	(627.005)	(559.594)
Above median	-0.020	-0.005	-0.152	-1.373	-187.079	-693.841
	(0.023)	(0.023)	(0.888)	(1.428)	(810.972)	(566.760)
VT × Above median	0.005	-0.014	-0.085	-0.794	121.734	343.189
	(0.023)	(0.023)	(0.903)	(1.572)	(754.027)	(646.305)
VTP	0.031*	0.025	1.573*	2.633*	599.328	844.741
	(0.018)	(0.020)	(0.835)	(1.495)	(638.502)	(733.479)
VTP × Above median	0.008	-0.055**	-0.303	-3.784**	291.438	-1235.764
	(0.025)	(0.025)	(1.132)	(1.731)	(853.501)	(799.320)
N	1,857	1,857	1,857	1,857	1,857	1,857

Notes: This table presents the differential ITT estimates of the impact of assigned treatment arms on whether the individual was employed in the beauty sector in self-employed work (column 1), and regular/salaried work (column 2) at the endline; the total number of days worked in the last 90 days (preceding the endline survey date) in the beauty sector in self-employed work (column 3) and regular/salaried work (column 4); the total earnings in the last 90 days (preceding the endline survey date) in the beauty sector in self-employed work (column 5) and regular/salaried work (column 6), by median cut of the number of treated individuals who were assigned their treatment group in the same month within a radius of 2km. Interaction terms capture differential effects on women who have higher (above median) number of treated individuals in their assigned treatment group in the same month within a radius of 2km. All specifications include baseline characteristics, training centre FE and quarter FE. The specifications also control for the number of registered women in the 2km radius of a woman's home in her training batch. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.18: Impact of skilling on psycho-social well-being and gender attitudes

	Job aspirations	Confidence	Decision-making	Mobility	Self-efficacy	Gender attitudes
	(1)	(2)	(3)	(4)	(5)	(6)
VT	-0.080*	-0.011	-0.062	-0.003	-0.084**	-0.022
	(0.041)	(0.032)	(0.041)	(0.029)	(0.037)	(0.031)
VTP	-0.009	0.016	-0.034	0.019	-0.027	-0.026
	(0.041)	(0.033)	(0.040)	(0.029)	(0.036)	(0.031)
VT = VTP [*p*-value]	[0.050]	[0.338]	[0.437]	[0.397]	[0.092]	[0.889]
N	1,857	1,857	1,857	1,857	1,857	1,857

Note: This table shows the ITT estimates for the effect of the treatment assignment on indices constructed using self-reported survey measures for job aspirations (column 1), confidence (column 2), decision-making within the household (column 3), mobility (column 4), self-efficacy (column 5), and gender attitudes (column 6). *Job aspiration* index consists of four questions: maximum salary/income the respondent expected with her current educational qualification/skills, whether she prefers outside home work over home-based work, whether she prefers full-time work over part-time work and whether she is willing to work in the next two years. For *confidence measures*, respondents had to respond either 'Yes', 'No' or 'Maybe' to questions asking them whether they are confident in certain tasks. 'Yes' responses have been recoded as 1, and 'No' and 'Maybe' have been recoded as 0. For *decision-making measures*, respondents were asked who was/were involved in decisions related to her education or skill choice, whether she can work outside home for a salary, who to marry, her own healthcare, and buying clothes for herself. Responses that included her as a decision-maker (either sole or joint) were recoded as 1, and those excluding her as one of the decision-makers were recoded as 0. The *mobility measures* consist of binary variables for whether a woman needs permission or can go alone to the following locations: health centre, relatives' or friends' home (in the neighbourhood), short distance (within city) by bus or three-wheeler, and long distance (like outside city) by train or bus. For *self-efficacy*, respondents were asked to what extent they agree with eight statements capturing beliefs about their capacity to execute behavior necessary to produce specific outcomes. The responses were 'Agree', 'Disagree' or 'Neither agree nor disagree'. Following Rosenberg's Self-Esteem Scale, for negative statements, 'Agree' was given 1 point, 'Neither agree nor disagree' 2 points, and 'Disagree' 3 points. The scores were reversed for positive statements. A higher score implies higher self-esteem. For *gender attitudes*, respondents either agreed or disagreed with eight statements - the responses have been recoded to reflect a more liberal gender attitude. All the indices are constructed using corresponding sub-measures, following Kling et al. (2007). The baseline control mean for all indices is zero. Equality of the VT and VTP coefficients is tested and the associated *p-values* are provided. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.19: Job search and perceptions about job opportunities

	Searched for a job	Online mode of job search	Number of job applications submitted	Number of job offers received	Availability of job opportunities in neighbourhood
	(1)	(2)	(3)	(4)	(5)
VT	-0.037	-0.002	-0.030	-0.030	-0.080
	(0.027)	(0.018)	(0.253)	(0.057)	(0.049)
VTP	-0.002	0.012	0.113	0.006	-0.089*
	(0.028)	(0.019)	(0.244)	(0.053)	(0.049)
VT = VTP [*p*-value]	[0.154]	[0.418]	[0.510]	[0.518]	[0.852]
N	1,857	1,857	1,857	1,857	1,857
Control Mean	0.13	0.04	0.22	0.05	2.99

Note: The table shows the ITT estimates for the effect of the treatment assignment on whether the individual searched for a job in the last 90 days (preceding the endline survey date) (column 1), whether they used an online mode for job search (column 2); the total number of job applications submitted (column 3), and the total number of job offers received (column 4) in the last 90 days (preceding the endline survey date); and their perception of availability of job opportunities in their neighbourhood (scale of 1-5; the higher the score, the better) (column 5). Control mean for column (5) is reported at the endline, whereas control means for columns (1)–(4) are reported at the baseline. Equality of the VT and VTP coefficients is tested and the associated *p-values* are provided. All specifications include baseline characteristics, training centre FE and quarter FE.Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.20: Impact of skilling on sources of job information

	Source of job information			
	Traditional network	Online job portals/websites	Institutions	Pamphlets/newspapers/ others
	(1)	(2)	(3)	(4)
VT	-0.033	-0.011	0.006	-0.001
	(0.023)	(0.007)	(0.006)	(0.005)
VTP	0.001	-0.005	0.005	-0.005
	(0.023)	(0.007)	(0.006)	(0.004)
VT = VTP [*p*-value]	[0.085]	[0.291]	[0.876]	[0.156]
N	1,857	1,857	1,857	1,857
Baseline Control Mean	0.12	0.00	0.00	0.00

Note: This table shows the ITT estimates for the effect of the treatment assignment across the two arms on whether they received job information for their current work at the endline using traditional network (column 1), online job portals/websites (column 2), institutions (column 3), and pamphlets/newspapers/other sources (column 4). Column 1 includes information from traditional network such as self, family, friends or acquaintances, coworker or employer, and neighbours; column 2 includes online job portals/websites like Naukri, Monster, Shine, etc. and websites like Twitter (now X), LinkedIn, company websites, etc; institutions in column 3 include NGOs, any skill training institutes, and fair/college placements; and column 4 includes information obtained from pamphlets, banners, newspapers and any other source not included in columns (1)–(3). Equality of the VT and VTP coefficients is tested and the associated *p-values* are provided. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.21: Labor market outcomes of household members of index woman

	Proportion of adult employed		Average maximum days worked by adult employed		Average earnings of adult employed	
	Male members of household	Female members of household	Male members of household	Female members of household	Male members of household	Female members of household
	(1)	(2)	(3)	(4)	(5)	(6)
VT	0.004	0.023*	0.624	1.628	1799.153	1089.088*
	(0.017)	(0.013)	(1.850)	(1.091)	(2132.897)	(579.447)
VTP	-0.017	0.023*	0.371	2.143*	-1671.808	540.037
	(0.017)	(0.014)	(1.844)	(1.106)	(2096.851)	(482.163)
VT = VTP [*p*-value]	[0.161]	[0.983]	[0.877]	[0.628]	[0.049]	[0.347]
N	1,857	1,857	1,857	1,857	1,857	1,857
Baseline Control Mean	0.63	0.15	54.70	12.72	18,145.61	2,536.50

Note: The table shows the ITT estimates for the effect of the treatment assignment on proportion of adult male members in the individual's household who were employed (column 1) and proportion of adult female members in the household who were employed (column 2) in the last 90 days (preceding the endline survey date); the average number of maximum days worked in either regular/salaried or self-employed work by adult employed male members in the household (column 3) and by adult employed female members in the household (column 4) in the last 90 days (preceding the endline survey date); the average earnings (in INR) of adult employed male members of the household (column 5) and adult employed female members of the household (column 6) in the last 90 days (preceding the endline survey date). Equality of the VT and VTP coefficients is tested and the associated *p-values* are provided. All specifications include baseline characteristics, training centre FE and quarter FE. Robust standard errors in parentheses; ***, **, * show significance at 1%, 5% and 10%, respectively.

B Cost-Benefit Analysis: Monetization of satisfaction

This calculation uses a benchmark value of £10,000 per well-being year (WELLBY), following HM Treasury (2021) and Fujiwara and Dass (2021), who estimate the monetary value of well-being using the willingness-to-pay (WTP) approach. A WELLBY is defined as a one-point increase in life satisfaction (on a 0–10 scale) for one person for one year. To contextualize this value for India, we scale the benchmark value of WELLBY using relative income levels. Our intervention increases the satisfaction among VTP participants by 0.14 points when we measure on the scale of 0 –10.

In 2019, GDP per capita in the UK was USD 42794, compared to USD 2041 in India, implying a ratio of 0.0476. Applying this ratio to the UK benchmark gives a WELLBY value of £476 for India, which converts to approximately USD 610 (using an exchange rate of £1 = USD 1.28 in 2019). Adjusting for purchasing power parity (PPP), with a PPP conversion factor of 20.2 for India in 2019, the WELLBY value becomes USD 30 in PPP terms.

Therefore, a 0.14-point gain in satisfaction is valued at $0.14 \times 30 \times 72 =$ INR 302 (in 2019 prices, using 72.15 INR/USD exchange rate). Adjusting for cumulative inflation of approximately 31.8% between 2019 and 2024, this gives a final value of INR 398 in 2024 prices.

This calculation rests on several key assumptions: (1) The monetary value of well-being is proportionally lower in poorer countries, based on income differences; (2) The marginal utility of income is similar across contexts when adjusted for PPP; (3) People in low-income countries place a similar relative value on well-being improvements; (4) There are no major cultural or institutional differences in how life satisfaction is perceived and reported across countries.