Digital Inclusion and Labor Market Performance: An Experimental Evaluation*

Miguel Almunia (CUNEF Universidad & CEPR)
Aleksei Samkov (Stanford GSB)
Tom Zohar (CEMFI)

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Abstract

The digital divide limits economic opportunities, particularly for older adults with low education who face barriers to accessing and using digital technologies. We evaluate a randomized intervention targeting disadvantaged individuals aged 45–64 in the Canary Islands, Spain. Over 2,900 participants were assigned to receive either a tablet with internet access, a tablet plus digital skills training, or no intervention. The combined treatment led to significant improvements in digital skills and job search behavior, though not in employment outcomes. Tablet-only recipients showed smaller gains, concentrated among those with low initial skills. These results suggest that bridging the digital divide requires not just access to technology but also targeted support to build digital capabilities.

Keywords: digital divide, social inclusion, digital skills, employability, randomized control trial.
JEL codes: J24, O33, I38, C93.

*Contact: miguel.almunia@cunef.edu, asamkov@stanford.edu, tom.zohar@cemfi.es.

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1 Introduction

The digital revolution has profoundly transformed economies worldwide, reshaping industries and accelerating innovation. By enabling faster and more efficient communication between economic agents, it has alleviated labor market frictions. Additionally, it has allowed public administrations to deliver better employment resources to unemployed citizens. However, these efficiency gains do not benefit everyone equally. Individuals without access to digital tools, often due to economic barriers like poverty or limited education, experience what is known as the "digital divide" (Van Dijk, 2020; Elena-Bucea et al., 2021). This inequality is further compounded by generational differences, as older individuals tend to have lower levels of digital literacy compared to younger generations, a phenomenon referred to as the *grey* digital divide (Mubarak and Suomi, 2022; He et al., 2022). These disparities highlight the need for targeted interventions to ensure that the advantages of the digital revolution are accessible to all segments of society.

This paper contributes to our understanding of how the digital divide can be narrowed by examining the role of two specific frictions: access to digital skills and access to digital equipment. For this purpose, we evaluate, through a randomized control trial (RCT), the effectiveness of an intervention designed to enhance digital skills and access among vulnerable populations. The intervention comprises two key components: the provision of digital devices (tablets) with internet access, and a digital skills course. Participants are randomly assigned to one of three experimental groups: one receiving only tablets with internet access (T1), another receiving both the tablets and digital skills training (T2), and a control group receiving neither. This design helps disentangle the impact of access to digital technology from that of digital skills training, allowing for a clearer assessment of the most effective approach to bridging the digital divide.

The intervention targets individuals aged 45 to 64 living in the Canary Islands, Spain, with up to secondary education, and who are recipients of income support programs. The final sample includes 2,966 individuals fulfilling these characteristics. The digital skills training was designed and implemented by EAPN Canarias, a non-profit organization, in collaboration with the Spanish Ministry of Social Inclusion.[1] Assignment to the three experimental arms was randomized by the General Secretariat for Inclusion (SGI) within geographic blocks, as we explain in more detail below.

The central hypothesis underlying this evaluation is that lack of digital skills constitutes a meaningful barrier to employment for this population. Under this premise,

[1]For more information on EAPN Canarias, visit https://eapncanarias.org. The intervention was funded by the NextGenerationEU program of the European Commission. The project implementation was supervised by the General Secretariat for Inclusion (SGI in Spanish), a branch of the Ministry of Inclusion, Social Security, and Migrations (MISSM).

an intensive, tailored training program—combined with access to an internet-connected device—can reduce that barrier by equipping participants with the competencies needed to search for jobs, engage with public employment services, and present themselves effectively to employers online. For this hypothesis to translate into employment gains, however, two conditions must hold. First, the lack of digital skills must be a binding constraint on employment for this population, conditional on their educational credentials, and age. Second, demand-side conditions must be sufficiently favorable to absorb newly upskilled workers. For older, low-educated job seekers, neither condition may be easily satisfied. Research on active labor market policies consistently finds limited short-term employment effects for training programs targeted at similar populations (Card et al., 2010, 2018), and field experiments document pervasive age discrimination in hiring that may prevent improved digital competencies from being recognized or rewarded in the labor market (Neumark et al., 2019). We return to this interpretation when discussing our employment results.

By contrast, the tablet-only treatment (T1) tests the impact of access to an internet-connected device without a supporting training program. This design allows us to examine whether access to technology alone can impact relevant outcomes such as digital skills, employability and labor market performance. We do not have a strong prior about T1's effects, and it is possible that the outcomes for T1 will be indistinguishable from those of the control group.

Our findings indicate that the main treatment group (T2), which received both tablets and digital literacy training, showed significant improvements in their self-reported digital skills and job search capabilities. These effects were sustained six months post-intervention, particularly among individuals with higher educational levels, suggesting that a basic level of education is crucial for acquiring new skills. Participants who only received the tablets (T1) also demonstrated modest improvements in digital literacy, suggesting that simply providing access to digital devices may offer some benefits. The latter effect is more pronounced for those who reported lower levels of digital skills in the baseline survey.

Although more than one-fourth of participants failed to respond to the endline survey, the results are robust to estimates that take into account sample attrition. In addition, compliance with the training treatment was relatively low: while almost nine out of ten participants in the tablet-only group collected their device, only two-thirds of those assigned to training started the course and fewer than half completed it. This reflects the substantial time commitment required—100 hours of classes and an internship—on top of caregiving and household responsibilities. Consequently, the estimated local average treatment effects on compliers (LATE) are about twice as large as the intention-to-treat

(ITT) estimates.

Despite the positive impact on digital skills and job search capabilities, we do not find any significant effects on employment outcomes in either treatment group. These null results admit two complementary interpretations. First, the absence of detectable short-term employment gains is consistent with the broader literature on active labor market policies (surveyed in Card et al., 2010, 2018), which finds limited short-run effects particularly for older workers. Second, our study was designed to detect employment effects of approximately 3.5 percentage points or larger, so we cannot rule out that the program produced a positive but statistically undetectable effect below that threshold. On the other hand, we do find significant improvements in self-reported life satisfaction in T2, even six months after the end of the intervention. This positive impact is possibly due to the situation of social exclusion that participants were exposed to before the intervention.

Our study contributes to a growing economics literature on digital inclusion interventions that aim to close the digital divide by improving both access to technology and the skills to use it. Early work on device provision finds that hardware alone rarely delivers downstream gains: randomized or natural experiments that supplied home computers or broadband—such as Malamud and Pop-Eleches (2011) in Romania, Fairlie and Robinson (2013) in California, and Cristia et al. (2017) with One Laptop per Child in Peru—documented some increase in cognitive skills and significantly higher computer use, but little effect on academic or labor outcomes. Broader evidence on broadband expansion (Czernich et al., 2011; Akerman et al., 2015; Hjort and Poulsen, 2019; Zuo, 2021) shows that connectivity can boost growth, employment, and wages, but these studies cannot isolate the role of individual digital skills. In contrast, research on adult digital-skills programs (Martínez-Alcalá et al., 2018) highlights that training can raise confidence and basic capabilities, though the evaluation has small sample size and is not tied to labor-market behavior. Together, these findings underscore that both access and skills matter, but rigorous evidence on how to combine them—particularly for disadvantaged adults—remains limited.

The study most closely related to ours is Barone et al. (2025). Their large-scale randomized program in Turin provided low-income families with free tablets, home internet, and digital-literacy courses. Consistent with our findings, it produced substantial improvements in digital skills, perceived future employment, and online engagement but no short-run employment gains. However, Barone et al. (2025) also enriches the literature in ways we do not, by focusing on family and parenting outcomes. Their household-oriented perspective allows them to study intergenerational effects—parents' involvement in children's education (digital parenting)—that lie outside the scope of our analysis.

Our paper complements these findings in three ways. First, we target a different population: economically vulnerable adults aged 45–64; a group largely absent from prior economics studies of digital inclusion yet often at the center of the grey digital divide. Second, we employ a three-arm randomized controlled trial that cleanly separates the effects of hardware access from those of intensive digital-skills training by including a tablet-only treatment group.[2] Third, while Barone et al. (2025) emphasize family dynamics, we focus on adult labor-market–relevant behaviors, documenting sizable improvements in job-search ability, digital proficiency, and life satisfaction even when employment levels remain unchanged.

Together, these contributions position our paper at the intersection between the education-focused device provision literature (Malamud and Pop-Eleches, 2011; Fairlie and Robinson, 2013; Cristia et al., 2017) and the emerging literature on the grey digital divide (Tsai et al., 2017; Martínez-Alcalá et al., 2018). By focusing on an older, labor-market-detached population and experimentally isolating the effects of access from those of training, we offer new causal evidence to inform the design of cost-effective digital inclusion strategies in high-income countries, where the digital divide increasingly affects older adults with low levels of education.

A second key contribution of the paper is to bridge two strands of literature that are often treated separately: the impact of digital interventions on employability, and the broader implications for subjective well-being. There is some evidence of negative impacts of internet connectivity, especially through social media, as reviewed in Aridor et al. (2024). In contrast, our findings suggest that digital training to older populations can yield meaningful improvements in perceived digital agency, and life satisfaction—even when employment effects are limited. This adds a new dimension to the literature by highlighting the non-pecuniary returns to digital literacy in marginalized adult populations. Furthermore, by documenting that these improvements are concentrated among those with only basic education levels, the paper also contributes to the understanding of heterogeneous returns to digital interventions. Taken together, our results underscore that digital inclusion strategies can improve well-being and reduce social isolation in vulnerable segments of the population, even when structural labor market barriers persist.

The rest of the paper proceeds as follows. Section 2 provides an overview of the experimental intervention and describes the sample of participants sample in the RCT. Section 3 outlines the experiment's objectives and our estimation strategy. Section 4 presents the results of the analysis, and Section 5 concludes.

[2]This design provides experimental evidence on whether devices alone can spark digital engagement—a question Barone et al. (2025) address only indirectly through mediation analysis. Both find similar results – hardware alone is useful, but there are large complementarities from a short course intervention.

2 Background, Implementation and Data

2.1 Target population

The Canary Islands is one of Spain's economically disadvantaged regions. In 2022, its GDP per capita was €22,100—approximately 23% below the national average of €28,750. The region also exhibited significantly higher rates of unemployment (17.6% vs. 13.0%) and poverty (36.3% vs. 26.3%) compared to the rest of the country (INE, 2024b,c,d). In parallel, national survey data reveal a pronounced digital divide across age groups: 44.4% of individuals aged 55 to 64 report having "no computer skills," compared to only 20.1% of those aged 25 to 34 (INE, 2024a).

Data from our own baseline survey helps further contextualize the exact nature of this digital divide for our target population. In terms of basic device availability, total internet isolation is rare: over 98% of our participants own a smartphone, meaning almost all enter the program with some baseline exposure to the internet. However, this exposure is largely restricted to basic communication and does not translate into the functional digital skills required for employability. For instance, prior to the intervention, only 66.5% of participants reported sending or receiving emails, and just 41.1% had downloaded or installed an application in the last 3 months. Furthermore, engagement with online administrative or employment tools was low; only 26.5% had used the internet to search for information on public administration websites, and just 33.3% had ever used it to search for jobs or submit a job application in the last 3 months. This highlights that despite possessing mobile internet access, this demographic severely lacks both the appropriate hardware (such as tablets or computers) and the foundational digital literacy necessary to actively participate in the modern labor market.

These regional and demographic disparities motivated the design of the intervention, which targeted individuals aged 45 to 64 living in the Canary Islands with low income and low levels of education. The goal was to improve their digital skills and provide them with practical tools that could enhance their access to labor market opportunities and digital public services.

2.2 Implementation Timeline and Randomization

The recruitment of participants was conducted by EAPN Canarias between November and December 2022. During this period, more than 10,000 recipients of the Minimum Income Scheme (in Spanish, *Ingreso Mínimo Vital*, IMV) or the Canarian Insertion Benefit (in Spanish, *Prestación Canaria de Inserción*, PCI) were contacted by telephone by a survey company.[3] Just under 3,000 individuals among this target population fulfilled the criteria to be included in the study stated above (i.e., being aged 45-64 and having less than complete secondary education) and also agreed to complete the baseline survey.

Randomization process. The randomization was done by the General Secretariat for Inclusion (SGI). The final sample of 2,966 individuals who completed the baseline was grouped into 65 blocks of approximately 45 individuals each, based on geographic proximity. These randomization blocks were designed to facilitate potential in-person participation in the training sessions. Within each block, individuals were randomly divided into three subgroups of roughly 15 participants. Each subgroup was then randomly assigned to one of the three experimental arms: Treatment Group 1 (T1, tablet only), Treatment Group 2 (T2, tablet plus digital skills training), or the Control Group (C).

This two-stage block randomization—first by location, then within-block assignment—was implemented to ensure both logistical feasibility and internal validity. In particular, it allowed participants in T2 to access nearby training centers, while preserving random assignment across all treatment arms. It also helped isolate the causal effects of tablet provision and digital training by holding local context constant within each block.

A potential concern with within-block randomization is the risk of spillover effects between treatment arms, either through contamination (e.g., control participants observing treated peers and seeking similar resources) or resentment. In our setting, we consider these risks to be minimal for two reasons. First, the treatment involved high-barrier, exclusive resources—specifically, the provision of hardware (a tablet with an internet connection) and access to a closed, customized 100-hour training course—which control participants could not easily replicate or access on their own. Second, the geographic blocks contained only about 45 participants each, drawn from a much larger pool of over 10,000 contacted individuals across populated areas. This low participant density makes it highly unlikely that control and treated individuals knew each other or interacted, acting as a natural safeguard against information spillovers.

Power Analysis. We complement our main results with a basic power analysis to assess the minimum detectable effects (MDEs) for our outcomes of interest. For a comparison between treatment (T) and control (C), the MDE is given by:

$$MDE = (z_{1-\alpha} + z_{1-\beta})\sigma\sqrt{\frac{1}{n_T} + \frac{1}{n_C}}$$

[3] Since March 2023, the PCI has been replaced by a similar program called the Canarian Citizenship Income (in Spanish, Renta Canaria de Ciudadanía, RCC). Since the PCI was in place when the sample selection for this project was implemented, we refer to the program as PCI throughout the paper.

where z denotes the critical values of the standard normal distribution, σ is the baseline standard deviation of the outcome, and n_T and n_C are the numbers of participants in the treatment and control arms, respectively. We set the significance level to $\alpha = 0.05$ (two-sided) and target power $1 - \beta = 0.80$, which are standard choices in experimental research.[4] The MDE estimates implied by our study design are reported in Table A1.

Start of the Intervention. In late January 2023, the intervention began with the distribution of internet-enabled tablets to all participants assigned to groups T1 and T2, and the delivery of a comprehensive digital skills training course to those in T2. Allowing participants to retain the tablets at the end of the project and covering internet service for 12 months were strategic decisions intended to sustain technology use and gauge longer-term training outcomes.[5] For T2, the intervention featured a comprehensive digital skills training course, totaling 100 hours (80 in-person and 20 virtual) over 10 weeks, followed by a 30-hour unpaid internship. The course was designed and delivered by EAPN Canarias.[6]

The training curriculum was structured around the European Digital Competence Framework (DigComp) to address multiple dimensions of digital literacy comprehensively. First, it taught participants how to search, evaluate, and manage digital information and data. Second, it covered digital communication and collaboration, including norms for online behavior. Third, the course emphasized safety, teaching students how to protect their devices, personal data, and digital well-being. Finally, they developed problem-solving skills to handle technical issues, use technology creatively, and identify gaps in their own digital competencies. This holistic foundation was designed to provide the necessary digital autonomy required for modern job search activities and employability, which participants could then put into practice during their internship. Participants completed internships across a variety of service-sector roles, including cleaning, caregiving for the elderly, horticulture and floriculture, retail customer service, food service in small restaurants, administrative support in nonprofit organizations and private sector institutions, and construction.

2.3 Data Sources

The primary data for this study were collected through self-administered phone surveys conducted at three distinct stages: a baseline survey prior to the intervention (Novem-

[4]This calculation provides a simple benchmark: it does not incorporate baseline covariates or clustering adjustments, both of which would typically reduce the detectable effect size.

[5]We cannot rule out that some participants may have lost or sold the tablet during the intervention period. If this were the case, our estimates should be considered a lower bound of the true effect of having the tablet.

[6]More information about the program can be found at https://redlabcanarias.org/.

ber–December 2022), a first endline survey shortly after the intervention (May–June 2023), and a second endline survey six months later to enable the analysis of the program's medium-term effects (November–December 2023). To encourage consistent participation, all study participants received a €30 supermarket voucher for completing the baseline phone survey and an additional €50 voucher after each of the two endline surveys. These surveys captured comprehensive information regarding participants' socio-demographic characteristics, self-reported digital skills, job search behaviors, and subjective well-being.

To complement the survey responses and objectively evaluate labor market impacts, we also utilize administrative data for the employment outcomes. The General Secretariat for Inclusion (SGI) facilitated the merging of our participant sample with anonymized, individual-level Social Security records containing detailed information on labor market spells. This is the same underlying data source from which the Continuous Sample of Employment Histories (Muestra Continua de Vidas Laborales) is extracted. Using these records, we construct an employment dummy taking a value of one if the individual was employed at any point in the six months prior to the intervention (and similarly, in the six months after). Furthermore, we compute the number of days worked over the previous six months and a work intensity index (ranging from zero to one) based on the share of days employed during this reference period. Finally, we include binary outcomes detailing the Social Security regime and the type of contract associated with the latest job spell observed in the reference period. Consistently, the correlation between these administrative records and our self-reported employment measures is 0.66.

2.4 Sample Description

Table 1 presents descriptive statistics for the full baseline sample of 2,966 individuals, providing a snapshot of the key characteristics of participants before the intervention. These statistics help contextualize the challenges faced by this population and justify the design of the program.

Demographics. About two-thirds of the participants were women, and they are almost equally distributed in the 45–54 and 55–64 age brackets. This age range was deliberately chosen to address the gray digital divide, wherein older adults are at greater risk of digital exclusion.

In terms of education, the study specifically targeted individuals with relatively low formal education to further address the gray digital divide. Consequently, participants with completed high school education or above were excluded, focusing the intervention on those with primary or secondary schooling.[7] Within the sample, any type of secondary ed-

[7] The survey screened out two groups: individuals who were illiterate (unable to read), and those with

ucation—whether incomplete, complete secondary, or incomplete high school—is grouped under the "secondary" category, while most participants report having completed only primary education.

Lastly, the geographic distribution shows that most participants reside in Gran Canaria (39.4%) and Tenerife (49.4%), the two most populous islands in the archipelago. Individuals from Fuerteventura, Lanzarote, and La Palma are grouped as "Other" due to their smaller representation in the sample. Although the program was also implemented on El Hierro and La Gomera, those two islands are excluded from the randomized evaluation because they lack sufficiently large samples to form viable experimental groups.

Income and Benefit Status. A large majority of participants (85.4%) report being unemployed, which was expected given the target population of recipients of income support transfers. This underscores the pressing need for interventions aimed at improving employability among this group.

All participants receive either the Minimum Income Scheme (IMV), the Canarian Insertion Benefit (PCI), or both—reflecting the economic vulnerability of the sample. The IMV is a national measure provided by the Spanish government to guarantee a basic income to individuals and families with insufficient financial resources. The PCI is a regional benefit specific to the Canary Islands, offering monetary assistance paired with complementary social-inclusion programs. In this study, 78.5% of participants received IMV and 32.1% received PCI (some individuals received both).

Digital Literacy and Well-being. To assess well-being, respondents rated both their health and life satisfaction on a scale from 1 ("not satisfied at all") to 5 ("very satisfied"). At baseline, the averages for both measures are close to 3, indicating moderate levels of self-reported well-being.

The study also incorporates three composite indicators—digital skills, job search ability, and e-government use—constructed from multiple survey questions and aggregated using the method proposed by Anderson (2008). To capture a comprehensive picture of participants' digital literacy, the digital skills measure captures self-reported confidence in internet navigation, autonomous technical problem-solving, and the ability to perform a wide range of specific tasks. These tasks range from basic smartphone usage (e.g., send-

completed high school (Bachillerato completo), vocational qualifications (Grado Medio), or university-level education (Universitario o Grado Superior). The six remaining categories—literate with no formal schooling, incomplete primary, complete primary, incomplete secondary, complete secondary, and incomplete Bachillerato—constitute our sample. For the balance tests, regression controls, and heterogeneity analysis, we aggregate these into three groups: Incomplete Primary (literate with no formal schooling or incomplete primary), Complete Primary (completed primary studies only), and Secondary Plus (any secondary schooling or incomplete Bachillerato).

ing emails, using messaging apps, downloading applications) to more advanced computer operations (e.g., managing files, using word processors and spreadsheets, and adjusting device configurations). The job search indicator captures the frequency and ability of participants to use the internet for job-related activities, such as searching online job portals, submitting applications, and looking for professional training opportunities. The e-government use indicator captures participants' engagement with online public administration services, such as accessing government websites, submitting official requests, and managing administrative procedures digitally. All three indicators are standardized with mean zero and a standard deviation of one (see Appendix B.2 for a complete list of survey components).

2.5 Balance Between Experimental Groups

Figure 1 shows the balance tests for the control group and each treatment group, with the corresponding values provided in Table A2. All data refer to the pre-intervention (baseline) survey.[8] For each variable, the mean values for the three groups are reported, along with the differences in means and the p-value from a difference-in-means t-test. For a design-consistent inferential check, Table A3 in the appendix reports the analogous tests with geographic node fixed effects and joint Wald tests with standard errors clustered at the node level.

Overall, the results suggest that the control and treatment groups are largely balanced across most variables, indicating that the random assignment successfully created comparable groups. A few individual differences are statistically significant: T2 has a higher proportion of English speakers than the control group (difference of 0.026, significant at the 10% level) and a lower share of PCI recipients (difference of -0.045, significant at the 5% level). The joint tests in Table A3 confirm this picture more formally. The T2-T1 comparison shows no significant joint imbalance ($p = 0.216$). For T2-C, the joint test is statistically significant ($p < 0.01$), consistent with the individual differences noted above. The T1-C joint test is also significant ($p < 0.01$), though no individual covariate is significant on its own, suggesting a diffuse rather than concentrated imbalance. These imbalances reflect small realized deviations in node composition rather than a failure of the randomization protocol. To address them directly, all outcome regressions include the full set of baseline covariates, including the baseline value of the dependent variable, and cluster standard errors at the randomization-block level, ensuring that inference is robust to any pre-existing differences between groups.

[8] As explained in Section 2.2, randomization was implemented within geographic blocks. In our outcome analyses we respect the design by clustering standard errors at that level and by controlling for a rich set of pre-treatment covariates, including the baseline value of the outcome.

2.6 Participation in the Intervention and Sample Attrition

Figure 2 provides an overview of the sample's participation in the intervention and attrition across the control group (C) and the two treatment groups (T1 and T2), with the corresponding values provided in Table A4. It shows how many participants were assigned to each group, how many started and completed the treatment, and how many responded to the endline surveys.

In the control group (C), all 986 participants who completed the baseline survey are considered to have "started and completed" the intervention, since there was no active treatment. In T1, 986 participants were assigned, and 89% both started and completed the treatment by collecting their tablet. In T2, 992 participants were assigned, but only 67% started the treatment and 42% completed it. We refer to this non-completion of treatment as non-compliance, which can lead to underestimation of the true average treatment effect when comparing T2 with the control group.

This relatively low compliance in T2 reflects the demanding nature of the training course, which required 100 hours of classes and a 30-hour internship. Many participants faced constraints such as caregiving responsibilities or reluctance to hire external caregivers despite being offered vouchers. As a result, while collecting a tablet required little effort in T1, the training program in T2 involved a substantial time commitment, which explains the drop in participation. This difference in compliance patterns is important for interpretation: outcomes in T2 reflect the effects for a motivated subset of participants, while T1 is closer to universal uptake.

To better characterize who does not comply, Table A5 examines the baseline predictors of each type of non-compliance separately. For tablet non-takeup — participants assigned to T1 or T2 who did not collect the device — the strongest predictors are being female and having care responsibilities (+4.4 and +6.0 percentage points (pp) respectively). This is consistent with the time constraints described above. Employment status also plays a role: working participants are more likely not to take up (+8.8 pp), while unemployed participants are less likely to opt out (–7.6 pp), reflecting differences in availability. For training non-completion among those who collected the tablet, care responsibilities again predict dropout (+10.4 pp), as do being an IMV recipient (–10 pp, i.e. lower dropout) and EU nationality (–15.5 pp). Together, these findings confirm that non-compliance is primarily driven by time and caregiving constraints rather than lack of interest or ability, and that compliers in T2 are a somewhat less constrained subset of the target population.

Although treatment completion varied across groups, a large share of participants still responded to the follow-up surveys. Among control group participants, 74% completed the first endline survey and 80% the second. In T1, completion rates were 80% and

82%, respectively, while in T2 they were 74% and 78%. These figures indicate that many individuals responded to the surveys even if they did not fully engage with the assigned treatment. This is explained by the survey firm's effort to contact all baseline respondents, regardless of their treatment compliance. Throughout the paper, we refer to non-response in either of the endline surveys as attrition.

To examine whether attrition—defined as a failure to respond to the first endline survey—is random or systematically related to treatment assignment, we regress attrition on indicators for T1 and T2, with the control group as the baseline (Table A6). The intercept of 0.261 indicates that 26.1% of control-group participants did not respond to the first endline. T1's coefficient of -0.056 implies a significantly lower attrition rate relative to the control group, whereas T2's coefficient of 0.001 is both small and statistically insignificant.

These findings align with the observed differences in participation and non-compliance: T1 required minimal commitment (collecting a tablet), whereas T2 involved a 10-week course and a 30-hour internship, leading to lower completion rates. Although participants were offered caregiver bonds to help with child or elder care, uptake was low, as many were reluctant to hire unknown caregivers. Overall, while T2 participants frequently did not complete the treatment, they still showed attrition rates similar to the control group, indicating that non-compliance did not necessarily translate into higher attrition.

Figure 3 examines whether attrition is correlated with specific baseline characteristics. For each characteristic X, we estimate a regression of the form:

$$\text{attrition}_i = \beta_0 + \beta_1 T1_i + \beta_2 T2_i + \gamma_0 X_i + \gamma_1 \big(X_i \times T1_i\big) + \gamma_2 \big(X_i \times T2_i\big) + \varepsilon_i. \quad (1)$$

Overall, most variables show no significant association with attrition, but there are several exceptions. In T1, English speakers and those caring for children or people with disabilities are more likely to drop out – likely reflecting time constraints. In T2, participants with a disability are less likely to drop out, while Spanish nationals have a higher attrition rate. Participants with secondary education in T2 also face lower attrition.

Although attrition appears largely random, these findings suggest certain subgroups are at greater risk of dropping out. To address this, we control for these characteristics in our analysis and apply the bounding method of Lee (2009) to evaluate the sensitivity of our results to selective attrition.

3 Empirical Analysis

3.1 Hypotheses

This section presents the key questions guiding our study. We investigate whether an intensive digital training program can reshape participants' technological behaviors and improve their employability, and whether simply providing tablets yields any discernible impact in the absence of a structured training component (pre-analysis plan at the AER registry – AEARCTR-0011811).

With Treatment Group 2 (T2), the intervention combines digital skills training with access to an internet-connected tablet, aiming to provide both the means and the know-how needed to participate effectively in the digital economy. The training is designed to improve participants' familiarity and confidence with digital tools, while the tablet ensures that these skills can be immediately applied outside the classroom. We hypothesize that this combination will not only enhance digital literacy but also translate into more effective behaviors, such as greater engagement in online job search, improved ability to prepare and submit job applications, and more efficient interaction with public services. Over time, these changes may support broader employability improvements by reducing digital barriers to labor market participation and social inclusion.

By contrast, the tablet-only treatment (T1) tests the impact of providing access to technology without accompanying training or support. This design allows us to assess whether simply lowering the hardware barrier—by giving participants a tablet with internet—leads to meaningful changes in digital skills, behaviors, or labor market outcomes. The intervention relies on participants' own initiative and ability to navigate and adopt digital tools independently.

3.2 Estimated Regressions

The regression model used to estimate causal effects in a randomized experiment is typically based on the difference in the outcome of interest between the treatment and control groups, assuming random assignment ensures statistical comparability. However, given we documented some imbalances—suggesting selective attrition for certain observables—there is a concern that unobserved characteristics may also influence attrition. To address this possibility, we control for the baseline value of the dependent variable in some specifications. This approach helps account for any initial differences between treatment and control groups. In addition, to improve the precision of estimates, we also present specifications that include a set of baseline controls, namely: gender, age (a binary indicator splitting the 45–64 age range into two groups: 45–54 vs. 55–64), Canarian Insertion

Benefit (PCI) receipt, Minimum Living Income (IMV) receipt, English proficiency, responsibility for caring for children or persons with disabilities, own disability status, education level, island of origin, nationality, and self-reported health status.

Formally, we measure intention-to-treat (ITT) impacts by estimating:

$$Y_{i1} = \alpha + \beta_1 T1_i + \beta_2 T2_i + \gamma Y_{i0} + X_i' \delta + \varepsilon_i \tag{2}$$

where Y_{i1} is the outcome of interest at endline, Y_{i0} is the corresponding baseline value; $T1_i$ and $T2_i$ are binary indicators for assignment to the tablet-only or tablet-plus-training groups, and X_i is the vector of control variables. Standard errors are clustered at the randomization-block level.

Following our pre-analysis plan, we divide our variables into primary and secondary outcomes. Our primary outcomes capture the direct technological aims of the intervention: (i) a composite indicator of digital skills ("Digital Skills"), (ii) a composite indicator of job search capability ("Job Search"), and (iii) a composite indicator of engagement with online public administration services ("E-Gov Use"). By aggregating several individual survey questions into three standardized composite indices using the method proposed by Anderson (2008), we inherently reduce the dimensionality of our outcome space, mitigating concerns regarding multiple hypothesis testing.

Our secondary outcomes capture broader socioeconomic effects, specifically: (iv) self-reported employment status ("Working"), and (v) self-reported life satisfaction ("Life Satisfaction"). For the medium-term analysis, we add three additional secondary employment outcomes: (vi) self-reported participation in any job training ("Job Training"), (vii) self-reported employment status conditional on being employed at the end of the experiment ("Job Retention"), and (viii) the self-reported number of months employed during the period. For detailed variable descriptions see Appendix B.

The coefficients of interest, β_1 and β_2, capture the causal effects of being assigned to receive a tablet and of being assigned to receive both a tablet and digital training, respectively, relative to the control group. These are intention-to-treat (ITT) estimates, since they reflect treatment assignment rather than actual take up of the intervention.

4 Main Results

In this section, we report the short- and medium-term effects of the intervention, using data from the first and second endline surveys (the latter conducted six months later). We then examine how the issues of attrition and non-compliance may affect our results. We also conduct heterogeneity analyses for the main results. Finally, we discuss the cost-effectiveness of such policy.

4.1 Short-term Effects

We estimate the effects of providing a tablet (T1) and a tablet plus digital training (T2) on participants': digital skills, job search ability, e-government use, life satisfaction, and employment status. Figure 4 offers a visual summary of these outcomes, while Table A8 details the corresponding regression coefficients in two specifications: one without controls and one that includes both controls and the baseline value of the outcome variable. The control variables, discussed in the previous subsection, include demographic and socio-economic characteristics.

Turning first to digital skills, the results show a positive and significant effect for both T1 and T2, although it is substantially larger for T2. In T1, the impact ranges from 0.14 to 0.18 standard deviations, whereas T2 yields an effect of about 0.50 to 0.52 standard deviations, significant at the 1% level in all specifications. This notable gap between the two treatment arms supports the hypothesis that an intensive digital training course has a more powerful effect on digital skills than simply providing tablet access. Importantly, these findings remain consistent when measured in the medium-term, six months after the intervention, although T2's effect size declines somewhat over time.

A similar pattern emerges for job search ability. Here, T2 shows a sizeable positive effect of 0.27 to 0.3 SD, (significant at 1% level) while T1 also yields a positive and statistically significant impact of 0.11 to 0.13 SD. The difference between T2 and T1 is statistically significant ($p = 0.001$), highlighting the additional value of structured digital training. Even tablet-only provision leads to measurable improvements in job search behavior, suggesting that access to appropriate hardware is itself a meaningful barrier. As with digital skills, these effects persist in the medium term.

For e-government use, the results reveal a stark contrast between treatment arms. T2 generates a significant increase of 0.16 to 0.20 SD (significant at 1% level), while T1 shows no discernible effect (-0.02 to -0.01 SD, not statistically significant). The difference between T2 and T1 is statistically significant ($p = 0.001$), suggesting that mere access to a device is insufficient to drive engagement with online public services—structured training is essential for this outcome.

In contrast, neither T1 nor T2 exerts a significant influence on self-reported employment in the short term: both sets of estimates are near zero and not statistically significant in all specifications. Several considerations bear on the interpretation of these null results. First, our study was powered to detect employment effects of approximately 3.5 percentage points or larger (see Section 4.3), so we cannot rule out that the program produced a positive but statistically undetectable effect below that threshold. Second, the absence of a detectable short-term employment effect is consistent with comprehensive meta-analyses of active labor market policies, which establish that training programs typically yield limited short-term employment effects, particularly for older workers (Card et al., 2010, 2018). Third, while our intervention successfully enhanced job search capabilities—a dimension of assistance often shown to outperform pure training (Crépon and van den Berg, 2016)—these behavioral improvements may be counteracted by structural demand-side barriers. Field experiments have documented pervasive age discrimination in hiring against older workers (Neumark et al., 2019), which may help explain why enhanced job-search effort and improved digital skills among our 45–64 age cohort did not translate into immediate, measurable labor market outcomes. Finally, for T2 specifically, participants devoted considerable time to training—10 weeks plus an internship—which may have reduced time available for job search or employment during the intervention period itself, further attenuating any short-term employment effect.

Regarding life satisfaction, there is a small but significant positive effect for T2, estimated at about 0.12 points on the 1–5 scale—corresponding to a 4% increase over the baseline mean of 2.9—while T1 shows no discernible impact. These magnitudes represent an increase of approximately 0.09 standard deviations (or roughly 0.17 standard deviations when adjusting for compliance in our IV estimates). To contextualize this magnitude, the empirical literature on subjective well-being frequently estimates that severe negative life events, such as job loss, reduce life satisfaction by roughly 0.3 to 0.5 standard deviations (Winkelmann and Winkelmann, 1998). Thus, the non-pecuniary gains from our digital inclusion intervention are substantial, equivalent in magnitude to offsetting roughly one-third to one-half of the well-being penalty typically associated with unemployment.

In summary, while the intervention had limited impact on short-term employment status for either T1 or T2, it yielded significant improvements in digital skills, job search ability, e-government use, and life satisfaction. Providing a tablet alone (T1) produced smaller but significant increases in both digital skills and job search ability, though it had no discernible effect on e-government use, employment, or life satisfaction. These results suggest that while tablet access alone can facilitate basic digital engagement and job search behavior, structured training is necessary to unlock gains in more complex digital tasks, such as navigating public administration services.

4.2 Medium-term Effects

Figure 4 presents results from the second endline survey, conducted six months after the intervention (i.e., medium-term). This follow-up was designed to determine whether the initially observed impacts persist or diminish over time. We report the primary specification for each outcome variable, including the full set of controls and the baseline value of each outcome (see Table A9 for further details).

Overall, the effects captured in this second endline are qualitatively similar to those in the first survey. Digital skills and job search effects persist for both treatment arms. E-government use effects also persist, with T2 maintaining a large and significant effect while T1 remains insignificant, mirroring the short-term pattern.

Regarding employment-related outcomes—such as the share of participants working, the number of months worked in the prior six months, or participation in job training—no significant effects are evident six months after the intervention. Among the 231 individuals who had reported employment during the first endline, an analysis of job retention likewise shows no significant impact of any treatment. In line with our pre-analysis plan, we also investigated additional labor market outcomes using administrative data from Social Security records, including days worked, employment intensity, contract type, and participation in different social security regimes.[9] All of these variables are calculated for two reference periods of six months before the start of the intervention and after its end. The results, reported in Table A10, likewise show no significant treatment effects across any specification.

Taken together, the persistence of null employment results across both self-reported and administrative measures admits two interpretations. On one hand, our study was only powered to detect employment effects larger than 3.5 percentage points, so smaller effects would remain undetectable even after six months. On the other hand, the sustained absence of measurable gains is consistent with structural demand-side barriers—such as pervasive age discrimination in hiring (Neumark et al., 2019)—that supply-side skill interventions alone may be insufficient to overcome, regardless of the time elapsed since training.

Finally, the short-term effects on life satisfaction for T2 sustain in the medium-term, while the effects of T1 catch-up. Remarkably, the magnitudes of the effects for T1 and T2 are very similar in the medium term (0.103 and 0.132 points, respectively), suggesting that much of the sustained improvement in subjective well-being is driven by the provision of the device and internet access itself, rather than the digital skills training. That said, these self-reported measures may be influenced by factors such as social desirability bias or experimenter demand effects, where participants might consciously or unconsciously report higher satisfaction to please the researchers who provided the devices; hence, caution is advised when interpreting these findings.

Minimal detectable effect (MDE): Table A1 reports the MDE estimates implied by our study design. For binary outcomes, the MDE is expressed both in probability

[9] The administrative data contain detailed information on labor market spells. This is the same data source used to construct the Continuous Sample of Working Lives *(Muestra Continua de Vidas Laborales)*, which has been used in multiple studies of the Spanish labor market.

units and in percentage points. These calculations indicate that the detectable effects for self-reported employment and life satisfaction are larger than the point estimates we obtain in our OLS and IV analyses, suggesting that, even if the intervention had some effect on these outcomes, its magnitude was too small to be reliably detected given our sample size. By contrast, the observed effects on digital skills, job search ability, and e-government use fall within the detectable range, consistent with the significant impacts documented above.

4.3 Mitigating Attrition and Non-Compliance

In our baseline specifications, we have not addressed the potential bias in the estimates due to the selective attrition documented in Figure 3 and substantial withdrawal from treatment among participants. To assess the potential impact of this selective attrition on the estimated effects, we implement the bounding method proposed by Lee (2009). Table A11 presents the estimated bounds for the effects on the five outcomes discussed above, and Figure 5 illustrates these bounds graphically. The results indicate considerable uncertainty regarding the magnitude and even the direction of T1's (tablet-only) effects on digital skills. By contrast, T2 shows more consistently positive effects across outcomes, which may partly be explained by the minimal trimming required for T2 (0.2%) compared with T1 (7.05%).

Additionally, we estimate both short-term and medium-term effects using an instrumental variables (IV) approach, in which random assignment to each treatment arm serves as an instrument for actual treatment take up. Participants who returned their tablets are treated as non-compliers, while those in T2 who did not complete the training but kept their tablet are considered compliers with respect to T1 but not T2. Under independence of assignment, the exclusion restriction, and monotonicity (no one moves from control to treatment, nor from T1 to T2), this strategy identifies the local average treatment effect (LATE) – the causal effect for compliers (Imbens and Angrist, 1994).

A key assumption for this IV approach is the exclusion restriction, which requires that random assignment to a treatment group affects our outcomes solely through the actual receipt of the treatment (i.e., collecting the tablet or completing the training). A potential violation of this restriction could occur if individuals assigned to T2 who failed to complete the training requirement felt discouraged, frustrated, or disengaged as a result of their non-compliance. If this psychological discouragement negatively affected their subsequent job search efforts or life satisfaction independently of the training itself, the exclusion restriction would be violated. While we do not consider this a severe threat to the validity of our estimates, it is important to explicitly acknowledge this potential channel when interpreting the LATE.

Formally, for each arm $j \in \{T1, T2\}$, let $Z_i^{(j)}$ denote assignment to j, $D_i^{(j)} \in \{0,1\}$ indicate receipt of j, and $Y_i(d)$ the potential outcome under $D_i^{(j)} = d$. Then

$$\tau_{LATE} \equiv \mathbb{E}[Y_i(1) - Y_i(0) | D_i^{(j)}(1) > D_i^{(j)}(0)]$$

We implement this with 2SLS using the assignment indicators $Z_i^{(j)}$ as instruments for the endogenous treatment indicators $D_i^{(j)}$.

Figure 4 and Tables A12–A13 present these IV results. As expected, the patterns observed in the ordinary least squares (OLS) analysis remain, but the IV effects are about twice as large, consistent with the fact that the LATE focuses on compliers, whereas the ITT estimates reflect average effects across all those assigned, regardless of compliance. Specifically, T1 and T2 both increase self-reported digital skills and job search ability, with T2 also generating significant improvements in e-government use; these gains persist in the medium term. Moreover, life satisfaction rises in the medium term for both treatment arms, again consistent with the OLS findings.

4.4 Heterogeneous Treatment Effects

To gain deeper insights into the intervention's impact across different social groups, we conducted several heterogeneity analyses, the full details of which are reported in the Appendix C. We tested both the pre-specified dimension of gender, as well as exploratory dimensions including education level, baseline digital skills, enrollment in the Canarian Insertion Benefit (PCI), and dependent status. Overall, these analyses reveal that treatment effects vary only mildly across most subpopulations.

However, a few patterns stand out. Following our pre-analysis plan, notable gender differences emerged in the medium term regarding labor market attachment and continued skill development (see Table A14). Specifically, women in both treatment groups exhibited significantly higher job retention rates compared to men six months post-intervention, and women in T2 showed a higher likelihood of participating in subsequent job training. Turning to our exploratory analyses, the provision of tablets alone proved especially beneficial for those with the most limited initial digital literacy. As shown in Figures A1-A2, T1 participants with the lowest baseline digital skills registered significantly larger short-term improvements in self-reported endline digital skills compared to higher quartiles. Finally, examining heterogeneity motivated by potential selective attrition, participants with a dependent—whether adult or minor—experienced larger short-term gains in digital skills from T2 than those without dependents (see Table A15). In the medium term, T2 participants with dependents were also more likely to be working, though T1 participants with dependents showed significantly lower job retention, presenting a more nuanced picture of how caregiving responsibilities interact with treatment effects (see Table A16).

4.5 Cost-Effectiveness

Evaluating the cost-effectiveness of this intervention is challenging for two reasons. On the cost side, the research team does not have access to detailed information on all the implementation-related costs. On the benefit side, the main indicators for which we find positive and significant effects are self-reported digital skills and life satisfaction, which are hard to quantify in monetary terms. Despite these limitations, we attempt to provide a rough comparison of the cost-effectiveness of the program.

We begin with the benefit side. Our estimation focuses on the impact on life satisfaction, since this indicator should theoretically encompass all the benefits of the intervention absent any significant employment effects. In order to quantify the welfare gains from the increase in life satisfaction, we take as a reference the guidance from the UK Treasury (MacLennan et al., 2021), which recommends valuing increases of 1 point in life satisfaction on a 0-10 scale at 13,000 GBP (about €15,000) per year.[10] Our main estimate of the positive effect on life satisfaction for T2 participants is 0.12 in the OLS specification (see Table A8b), which corresponds to the intention-to-treat estimate. We do not consider the IV estimates in this calculation because they provide a measure of the average treatment effect on compliers, which is a particular subsample with potentially different characteristics. Since our life satisfaction measure is on a 1-5 scale, the estimated effect corresponds to 0.264 points on a 0-10 scale.[11] Thus, we estimate that the monetary gains *per capita* for the increase in self-reported life satisfaction for a period of one year would be €3,960. Considering that the estimate is based on the 736 participants from T2 who responded to the first follow-up survey, the aggregate gain would be approximately €2.9 million.

On the cost side, as mentioned above, we do not have detailed information. Thus, we begin our estimation from the aggregate cost of the intervention, which is reported to have been €8 million, of which 25% was devoted to the evaluation and the rest to the implementation (MISSM, 2025). Of the €6 million that correspond to the intervention, we subtract €400,000 that correspond to the cost of the tablets with internet connection given to participants in the T1 group.[12] Therefore, we arrive at a rough estimate of

[10] These estimates have been used in other contexts, see Bagues and Dimitrova (2025).

[11] The 1-5 scale has 5 possible values and the 0-10 scale has 11 possible values, so we calculate $0.12/(5/11) = 0.264$.

[12] As a rough approximation, the cost of the tablets was about €200, and we estimate another €200 for the 12-month internet connection. We multiply this by the number of participants assigned to T1, which is 988.

€5.6 million for the cost of delivering the program for T2 participants, which includes: the tablets for this group, the salaries of the 60+ facilitators of the training program, the rental cost of premises for the 60+ groups, general management costs, and other implementation costs.

These figures suggest that the program was not cost-effective: the estimated aggregate benefit of approximately €2.9 million falls short of the estimated implementation cost of €5.6 million by a factor of roughly two. However, we would like to emphasize again that all the estimates in this subsection should be treated with caution given the uncertainty around them.

5 Conclusion

This paper has presented a comprehensive evaluation of a randomized controlled trial aimed at addressing the digital divide and enhancing digital skills among disadvantaged individuals in the Canary Islands. Participants were divided into three groups: one received tablets with internet access (T1), another received both tablets and a digital skills training course (T2), while a third group served as the control.

Our results indicate that the intervention successfully improved digital skills and job search capabilities, particularly for those who underwent the intensive digital training. In addition, we found that the provision of tablets proved notably effective for individuals with lower baseline digital literacy. However, no significant impact on employment was observed in either treatment group, even after six months, although it did have a positive impact on life satisfaction for participants receiving digital training. Medium-term outcomes, assessed through administrative data and a second survey six months post-intervention, mirrored the short-term effects and were more sustained among participants with higher educational levels.

These findings suggest that tailored training programs can improve intermediate outcomes such as digital skills and job search intensity, consistent with prior evidence on digital training among disadvantaged populations (Martínez-Alcalá et al., 2018; Tsai et al., 2017). At the same time, the high non-completion rate in the tablet-plus-training group (T2) highlights the importance of accounting for attrition in the design and implementation of such interventions. Finally, the null employment effects indicate that gains in intermediate outcomes do not automatically translate into labor market improvements.

Looking ahead, the results provide a mixed message regarding the desirability of scaling up the intervention. The positive impacts on digital skills, job search ability, and life satisfaction support the case for broader deployment, both within the Canary Islands and in other regions facing similar challenges. However, our rough cost-effectiveness analysis suggests that the estimated aggregate welfare gains fall short of implementation costs, albeit with substantial uncertainty on both estimates. Taken together, the evidence points to the need for a more carefully targeted program design, building on the effectiveness of providing devices to individuals with low baseline digital literacy while also addressing the noncompliance problems and high overall implementation costs.

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Tables

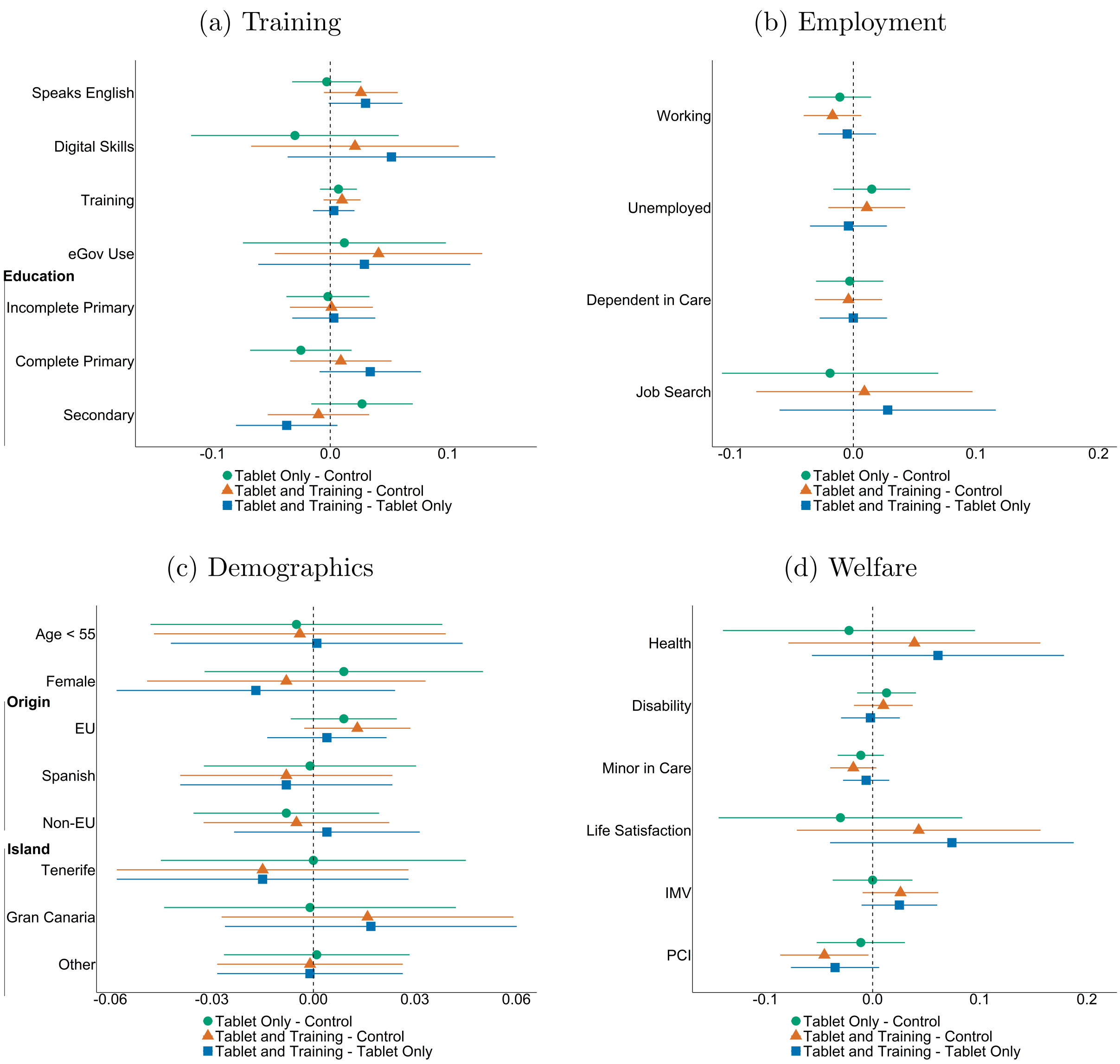
Table 1: Descriptive statistics of the sample at baseline

	Variable	Mean	Std. Dev.	Min.	Max.	Obs.
	Female	0.653	0.476	0	1	2966
	Age <55	0.450	0.498	0	1	2966
	English Speaker	0.138	0.344	0	1	2966
	Working	0.083	0.276	0	1	2966
	Unemployed	0.855	0.352	0	1	2966
	Dependent in Care	0.112	0.316	0	1	2966
	Minor in Care	0.064	0.245	0	1	2966
	Disability	0.110	0.313	0	1	2966
	Training	0.035	0.184	0	1	2966
	Health	2.959	1.335	1	5	2966
	Life Satisfaction	3.039	1.291	1	5	2966
	Digital Skills	0	1	−2.155	5.090	2966
	Job Search	0	1	−1.237	1.912	2966
	E-Gov Use	0	1	−1.022	5.784	2966
	PCI	0.321	0.467	0	1	2966
	IMV	0.786	0.41	0	1	2966
Island	Other	0.112	0.315	0	1	2966
	Gran Canaria	0.394	0.489	0	1	2966
	Tenerife	0.494	0.5	0	1	2966
Nationality	Spanish	0.859	0.348	0	1	2966
	EU	0.038	0.191	0	1	2966
	Non-EU	0.103	0.304	0	1	2966
Education	Incomplete Primary	0.189	0.392	0	1	2966
	Complete Primary	0.376	0.484	0	1	2966
	Secondary	0.435	0.496	0	1	2966

Notes: "Digital Skills" and "Job Search" are composite indicators computed using the method developed by Anderson (2008). See the Appendix for details on the construction of these indicators. IMV and PCI refer to the Minimum Income Scheme and the Canarian Insertion Benefit, respectively.

Figures

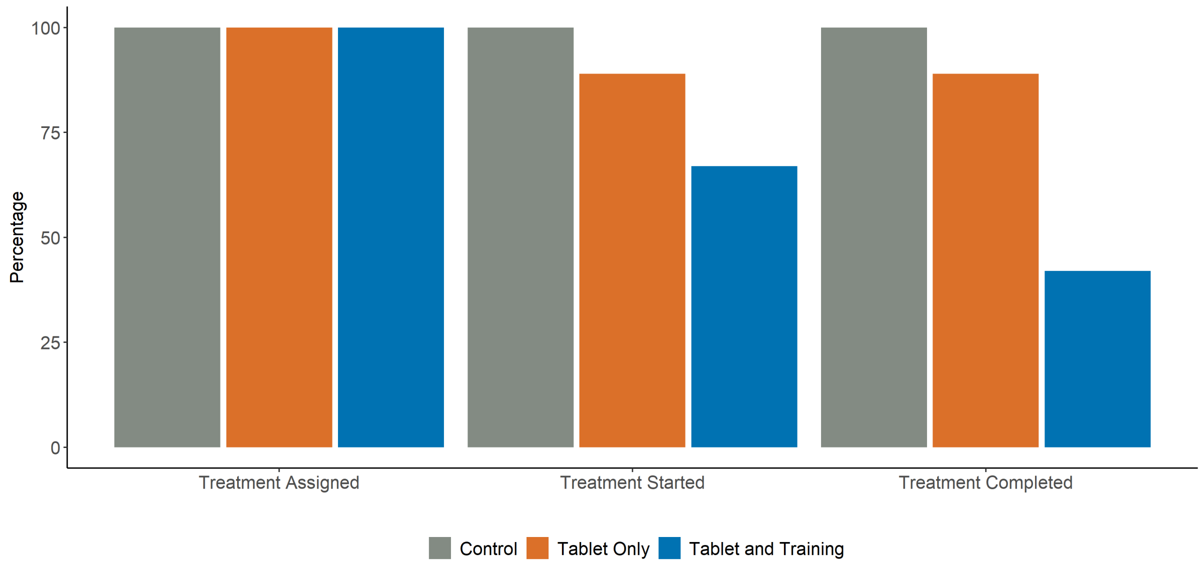
Figure 1: Balance between experimental groups at baseline



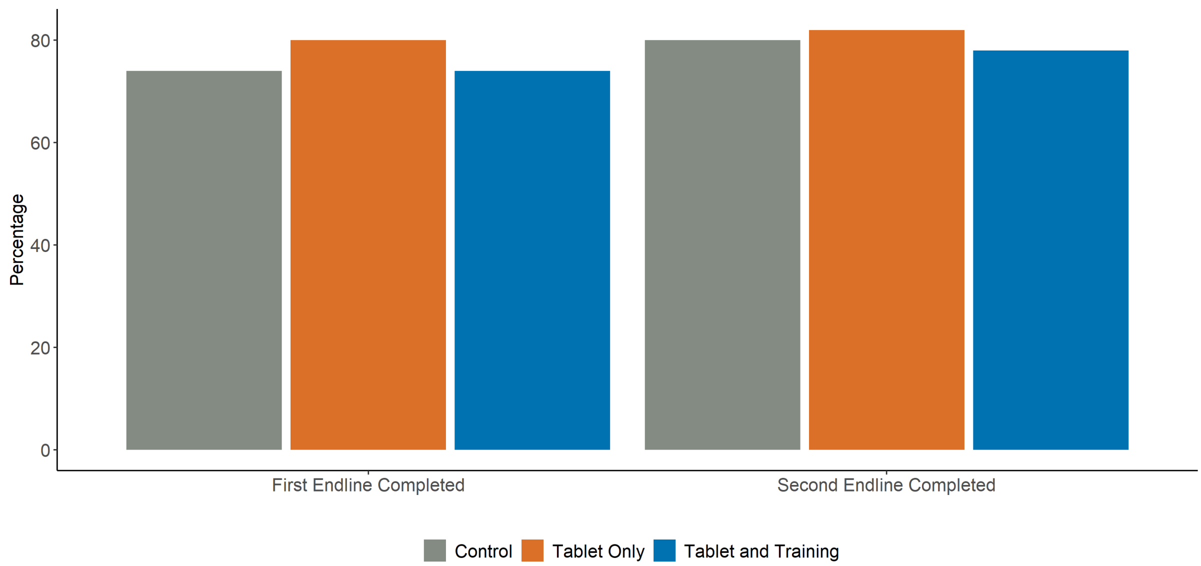
This plot displays the differences of baseline characteristics among the control group, the tablet-only group (T1), and the tablet + training group (T2). It is divided into four panels: Panel 1a presents training-related variables; Panel 1b displays work-status variables; Panel 1c shows demographic variables; and Panel 1d illustrates welfare status. This plot corresponds to columns (4), (5), and (6) in Table A2 and is intended to highlight the baseline balance among the three groups. Note that each estimator is accompanied by a 95% confidence interval. Randomization was implemented within geographic blocks; the differences shown here are unadjusted and should be interpreted descriptively. All outcome analyses in the paper include baseline covariates and cluster standard errors at the randomization block level to ensure inference consistent with the randomization design.

Figure 2: Attrition and Compliance Rates by Experimental Group

(a) Treatment Compliance

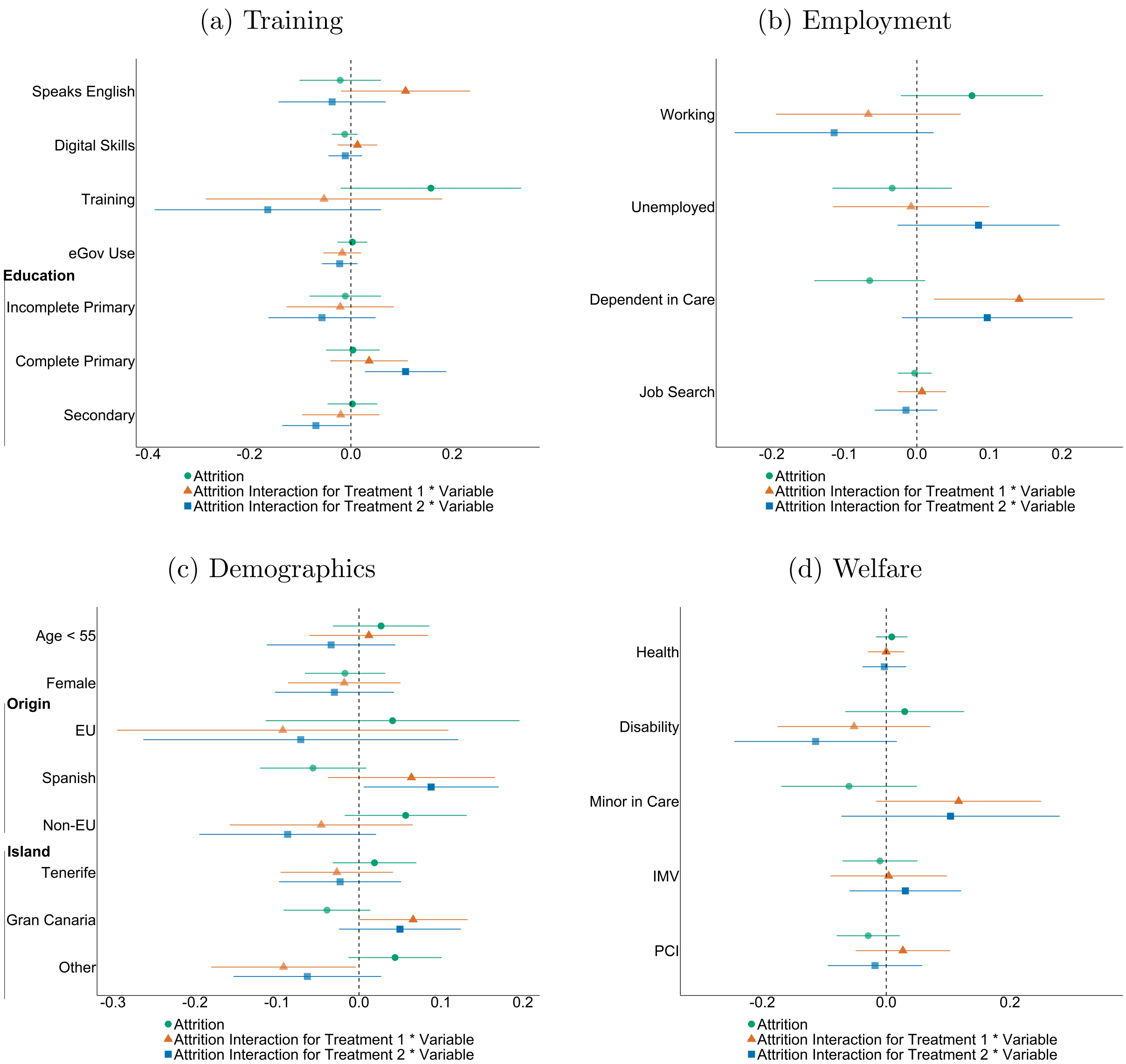


(b) Completion of Endline Surveys



Notes: This plot shows participation across three groups – Tablet Only (T1), Tablet + Training (T2), and the Control group – over different stages. Panel (a) illustrates treatment compliance during the three stages, while Panel (b) displays the share of participants within each treatment arm who responded to surveys immediately after the treatment and six months later. Orange bars represent the Tablet Only group (T1), blue bars indicate the Tablet + Training group (T2), and gray bars correspond to the Control group.

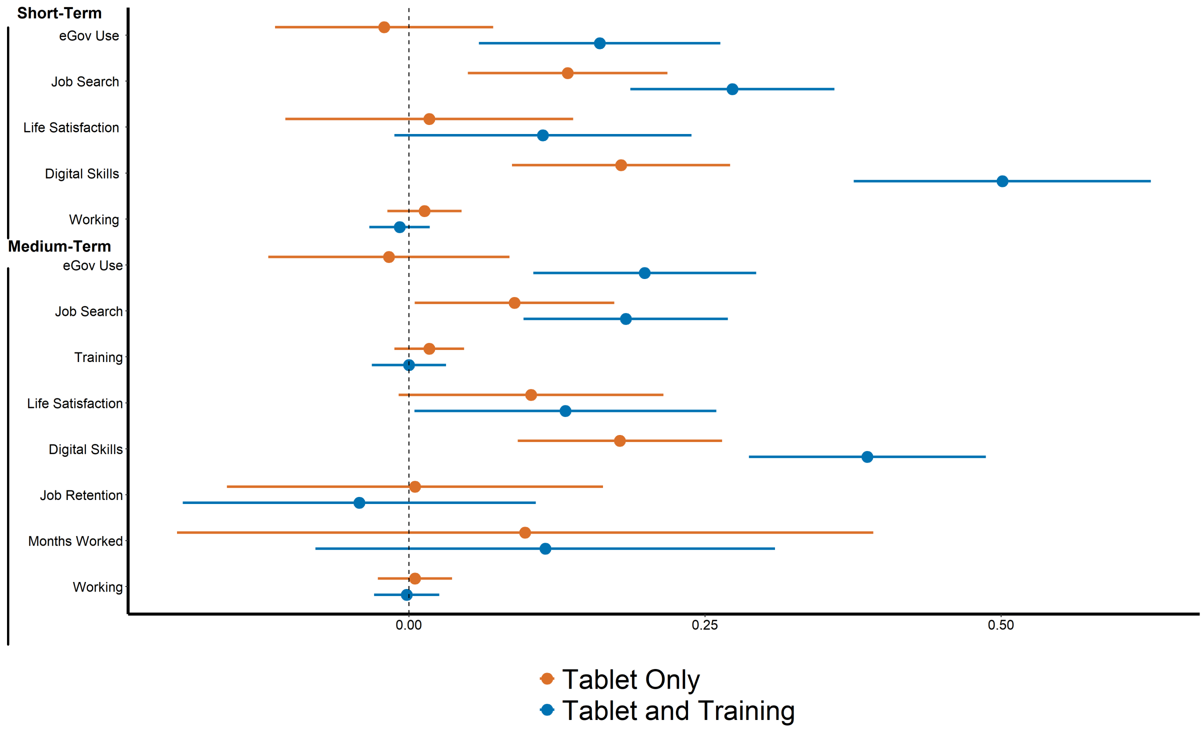
Figure 3: Selective attrition between treatment groups



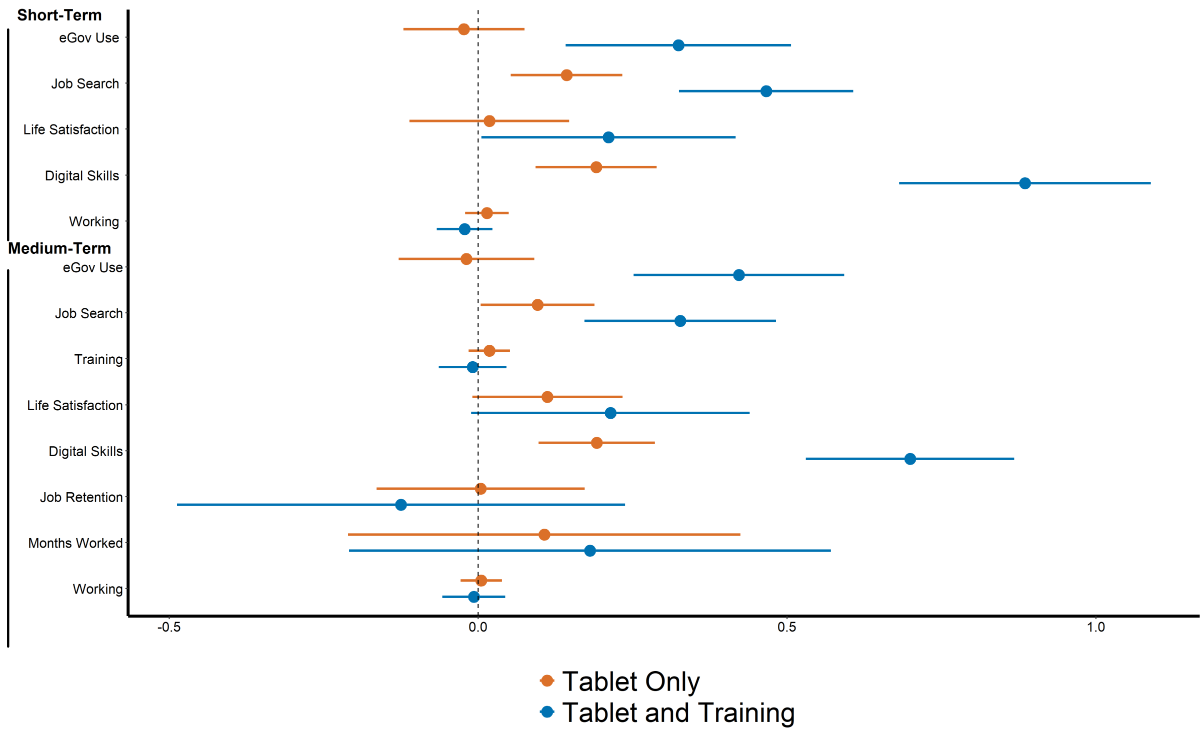
Notes: This figure displays differences in attrition by treatment arm for a range of control variables, grouped into four panels. Panel 3a covers education and training (e.g., highest academic level), Panel 3b focuses on work-related variables, Panel 3c examines demographic characteristics, and Panel 3d shows welfare characteristics (health status, life satisfaction, etc.). Each point represents the estimated coefficient with its 95% confidence interval. This figure corresponds to Table A7.

Figure 4: Main Results: Short- and Medium-Term Effects

(a) OLS Regression

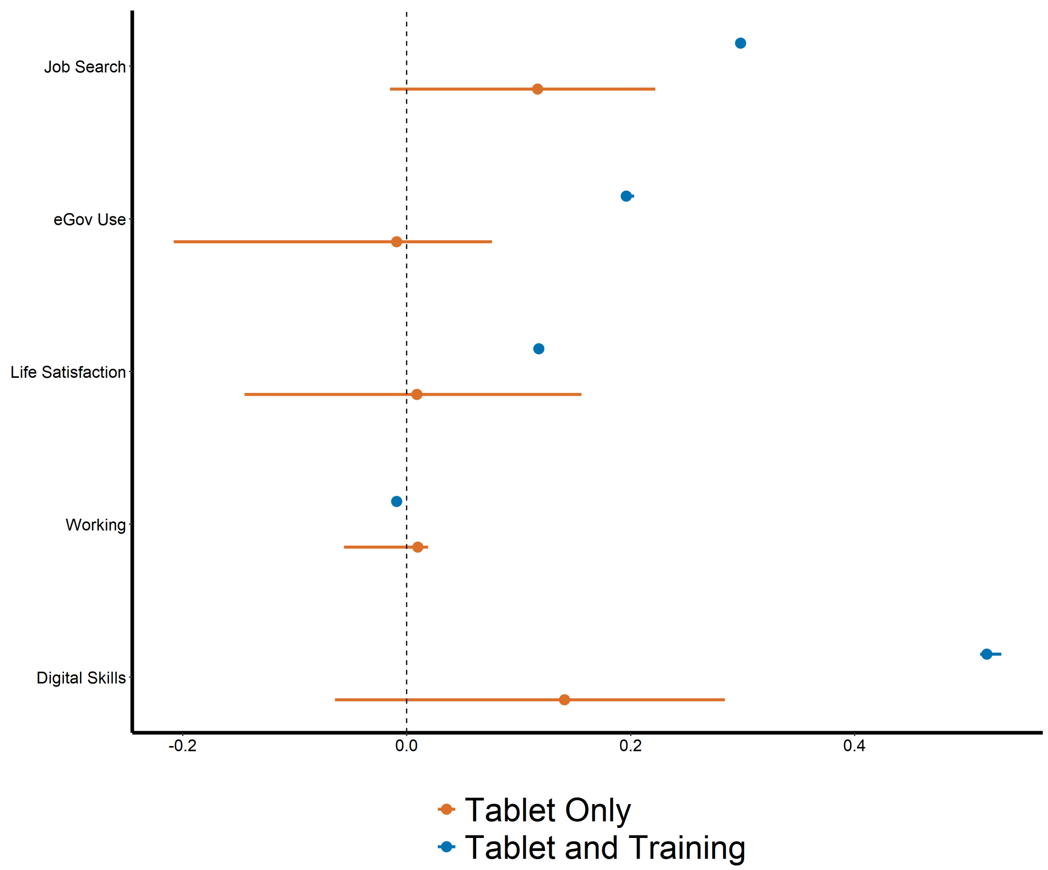


(b) IV Regression



Notes: This figure shows the short-term (top) and medium-term (bottom) effects of two interventions on several self-reported outcomes. Orange lines represent T1 (tablet only), and blue lines represent T2 (tablet plus training). Dots indicate point estimates, and lines show 95% confidence intervals. Short-term estimates are presented in Tables A8 and A12; medium-term estimates appear in Tables A9 and A13.

Figure 5: Lee (2009) Bounding Method for the Effects on Key Outcomes



Notes: This figure displays the Lee (2009) bounds on the treatment effects for five key outcomes: Digital Skills, Job Search, e-Government use, self-reported employment (Working), and Life Satisfaction. For each outcome and each treatment arm (T1–C and T2–C), the point shows the raw difference in means, and the horizontal line spans the lower to upper bound derived from the Lee (2009) trimming procedure, which accounts for the potential bias introduced by selective attrition. The bounds are constructed by trimming the upper or lower tail of the outcome distribution in the group with lower attrition to match the attrition rate of the other group. The T2 bounds are nearly identical to the raw means, as attrition rates in T2 and the control group are very similar. "Digital Skills" and "Job Search" are composite indicators constructed using the method of Anderson (2008). "Working" is an indicator for self-reported employment. "Life Satisfaction" is measured on a scale from 1 to 5.

Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement

All data, both raw and processed, for this paper are kept at the Ministerio de Inclusión, Seguridad Social y Migraciones. The data used in this paper are only available to the researchers through a virtual desktop at the Ministerio's server, after being anonymized, and they cannot be downloaded. The results can be downloaded after verification by the Ministerio. The researchers can only use these data for the purpose of the evaluation implemented in this paper. The researchers have signed an agreement with the Ministry that indicates that they cannot share any of these data through any means and the Ministerio has not indicated their willingness to share the data with journal editors or referees for the purpose of refereeing the paper for its potential publication.

Appendix

A Appendix Tables and Figures

Table A1: Minimal Detectable Effects (MDEs) at $\alpha = 0.05$, 80% power

Outcome	Baseline SD	MDE (T1 vs C)	MDE (T2 vs C)
Working	0.276	0.03481	0.03477
Life Satisfaction	1.291	0.16281	0.16265
Digital Skills	1.000	0.12611	0.12599
Job Search	1.000	0.12611	0.12599
E-Gov Use	1.000	0.12611	0.12599

Notes: MDEs are computed using $MDE = (z_{1-\alpha/2} + z_{1-\beta})\,\sigma\sqrt{\frac{1}{n_T} + \frac{1}{n_C}}$, with $\alpha = 0.05$ (two-sided) and $1 - \beta = 0.80$. Reported SDs come from baseline descriptive statistics. Calculations do not incorporate covariates or clustering adjustments, so reported values provide a conservative benchmark.

Table A2: Balance Test Between Experimental Groups

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Control: Mean	T1: Mean	T2: Mean	T1 − Control	T2 − Control	T2 − T1
Female	0.653	0.662	0.645	0.009	−0.008	−0.017
				(0.021)	(0.021)	(0.021)
Age <55	0.453	0.448	0.450	−0.005	−0.004	0.001
				(0.022)	(0.022)	(0.022)
Speaks English	0.130	0.127	0.156	−0.003	0.026*	0.030*
				(0.015)	(0.016)	(0.016)
Working	0.092	0.081	0.076	−0.011	−0.017	−0.005
				(0.013)	(0.012)	(0.012)
Unemployed	0.846	0.861	0.857	0.015	0.011	−0.004
				(0.016)	(0.016)	(0.016)
Dependent in Care	0.115	0.111	0.111	−0.003	−0.004	0.000
				(0.014)	(0.014)	(0.014)
Minor in Care	0.074	0.063	0.056	−0.011	−0.018	−0.006
				(0.011)	(0.011)	(0.011)
Disability	0.102	0.115	0.113	0.013	0.010	−0.002
				(0.014)	(0.014)	(0.014)
Training	0.029	0.036	0.039	0.007	0.010	0.003
				(0.008)	(0.008)	(0.009)
Health	2.953	2.931	2.992	−0.022	0.039	0.061
				(0.060)	(0.060)	(0.060)
Life Satisfaction	3.034	3.004	3.078	−0.030	0.043	0.074
				(0.058)	(0.058)	(0.058)
Digital Skills	0.003	−0.027	0.024	−0.030	0.021	0.052
				(0.045)	(0.045)	(0.045)
Job Search	0.003	−0.016	0.012	−0.019	0.009	0.028
				(0.045)	(0.045)	(0.046)
E-Gov Use	−0.018	−0.006	0.023	0.012	0.041	0.029
				(0.044)	(0.045)	(0.046)
PCI	0.340	0.329	0.294	−0.011	−0.045**	−0.035*
				(0.021)	(0.021)	(0.021)

IMV	0.777	0.777	0.802	0.000	0.026	0.025
				(0.019)	(0.018)	(0.018)
Island						
Tenerife	0.499	0.499	0.484	0.000	−0.015	−0.015
				(0.023)	(0.022)	(0.022)
Gran Canaria	0.389	0.389	0.405	−0.001	0.016	0.017
				(0.022)	(0.022)	(0.022)
Other	0.112	0.112	0.111	0.001	−0.001	−0.001
				(0.014)	(0.014)	(0.014)
Nationality						
Spanish	0.862	0.861	0.854	−0.001	−0.008	−0.008
				(0.016)	(0.016)	(0.016)
EU	0.030	0.039	0.043	0.009	0.013	0.004
				(0.008)	(0.008)	(0.009)
Non-EU	0.108	0.099	0.103	−0.008	−0.005	0.004
				(0.014)	(0.014)	(0.014)
Education						
Incomplete Primary	0.190	0.187	0.191	−0.002	0.001	0.003
				(0.018)	(0.018)	(0.018)
Complete Primary	0.381	0.356	0.390	−0.025	0.009	0.034
				(0.022)	(0.022)	(0.022)
Secondary	0.429	0.456	0.419	0.027	−0.010	−0.037*
				(0.022)	(0.022)	(0.022)
Joint F-test p-value				0.664	0.278	0.217
Observations	986	988	992			

Notes: This table displays baseline characteristics and differences between control, treatment group 1 (T1), and treatment group 2 (T2). "Digital Skills" and "Job Search" are composite indicators computed using the method developed by Anderson (2008). See the Appendix for details on the construction of these indicators. IMV and PCI refer to the Minimum Income Scheme and the Canarian Insertion Benefit, respectively. Differences between treatment groups and control are provided, with standard errors in parentheses. Randomization occurred within geographic nodes, but these balance tests are based on unadjusted differences in means and should be interpreted descriptively. In all subsequent outcome regressions, we include baseline covariates (including the baseline value of the dependent variable) and cluster standard errors at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A3: Balance Test Between Experimental Groups (FE-corrected)

Variable	T1 − Control	T2 − Control	T2 − T1
Female	0.007	−0.011	−0.018
	(0.024)	(0.030)	(0.031)
Age < 55	−0.005	−0.005	0.000
	(0.021)	(0.022)	(0.023)
Speaks English	−0.003	0.027	0.030*
	(0.015)	(0.018)	(0.017)
Working	−0.011	−0.018	−0.006
	(0.014)	(0.013)	(0.011)
Unemployed	0.014	0.009	−0.005
	(0.018)	(0.017)	(0.015)
Dependent in Care	−0.002	−0.002	0.000
	(0.013)	(0.016)	(0.014)
Minor in Care	−0.011	−0.015	−0.004
	(0.012)	(0.013)	(0.011)
Disability	0.012	0.011	−0.002
	(0.013)	(0.012)	(0.014)
Training	0.007	0.010	0.003
	(0.008)	(0.009)	(0.009)
Health	−0.021	0.030	0.051
	(0.054)	(0.055)	(0.062)
Life Satisfaction	−0.030	0.032	0.062
	(0.057)	(0.058)	(0.056)
Digital Skills	−0.040	0.012	0.052
	(0.047)	(0.045)	(0.049)
Job Search (alt.)	−0.019	0.008	0.027
	(0.045)	(0.045)	(0.053)
E-Gov Use	0.011	0.033	0.022
	(0.047)	(0.052)	(0.052)
PCI	−0.016	−0.046	−0.030
	(0.027)	(0.031)	(0.028)

IMV	0.005	0.024	0.020
	(0.026)	(0.032)	(0.028)
Island			
Tenerife	−0.001	−0.015	−0.014
	(0.003)	(0.015)	(0.015)
Gran Canaria	0.000	0.014	0.014
	(0.003)	(0.015)	(0.015)
Other	0.001	0.001	0.000
	(0.001)	(0.001)	(0.002)
Nationality			
Spanish	0.001	−0.005	−0.007
	(0.016)	(0.019)	(0.017)
EU	0.009	0.013	0.004
	(0.009)	(0.009)	(0.008)
Non-EU	−0.010	−0.007	0.002
	(0.015)	(0.017)	(0.015)
Education			
Incomplete Primary	−0.005	−0.001	0.004
	(0.019)	(0.017)	(0.016)
Complete Primary	−0.024	0.006	0.030
	(0.022)	(0.022)	(0.021)
Secondary Plus	0.029	−0.006	−0.035
	(0.025)	(0.024)	(0.022)
Joint F-test p-value	0.000***	0.000***	0.216
Observations	1,974	1,978	1,980

Notes: This table displays within-node differences in baseline characteristics between treatment and control groups, estimated by regressing each covariate on a treatment indicator and geographic node fixed effects using the relevant pairwise subsample. Standard errors, clustered at the node level, are in parentheses. "Digital Skills" and "Job Search" are composite indicators computed using the method developed by Anderson (2008). See the Appendix for details on the construction of these indicators. IMV and PCI refer to the Minimum Income Scheme and the Canarian Insertion Benefit, respectively. The joint F-test p-value tests the null that treatment assignment is jointly orthogonal to all baseline covariates conditional on node fixed effects. In all subsequent outcome regressions, we include baseline covariates (including the baseline value of the dependent variable) and cluster standard errors at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A4: Dropout and Attrition Rates by Experimental Group

Group	Treatment assigned	Treatment started	Treatment completed	First Endline completed	Second Endline completed
C	986	986	986	729	785
	(100%)	(100%)	(100%)	(74%)	(80%)
T1	988	880	880	786	811
	(100%)	(89%)	(89%)	(80%)	(82%)
T2	992	664	412	732	774
	(100%)	(67%)	(42%)	(74%)	(78%)
Total	2966	2530	2278	2247	2370

Notes: The table presents attrition rates by experimental group, tracking the progression of participants from treatment assignment to various study stages. It includes the control group (Control) and two treatment groups (T1 and T2). "Treatment assigned" denotes the initial number of participants assigned to each group, while "Treatment Started" represents those who began the assigned treatment. "Treatment Completed" reflects those who successfully completed the treatment. "First Endline completed" shows the number and percentage of participants completing the first endline survey, and "Second Endline completed" presents the same for the second endline survey implemented six months later.

Table A5: Correlates of Treatment Non-Compliance by Type

Control Variable	Tablet Non-Takeup	Training Non-Completion
T2 Assignment	0.222***	
	(0.023)	
Female	0.044**	−0.021
	(0.018)	(0.037)
Age < 55	0.013	−0.002
	(0.020)	(0.030)
Speaks English	−0.041	−0.034
	(0.031)	(0.050)
Working	0.088**	0.060
	(0.040)	(0.079)
Unemployed	−0.076**	−0.048
	(0.035)	(0.062)
Dependent in Care	0.060*	0.104*
	(0.031)	(0.062)
Minor in Care	−0.011	−0.069
	(0.036)	(0.067)
Disability	−0.032	0.006
	(0.028)	(0.057)
Training	0.058	−0.035
	(0.047)	(0.084)
Health	−0.008	0.003
	(0.006)	(0.014)
Life Satisfaction	0.004	0.007
	(0.007)	(0.016)
Digital Skills	−0.006	−0.013
	(0.009)	(0.020)
Job Search	−0.015*	−0.016
	(0.009)	(0.021)
E-Gov Use	−0.009	−0.025
	(0.007)	(0.017)
PCI	−0.044**	0.033
	(0.019)	(0.038)
IMV	0.038	−0.100**

	(0.025)	(0.042)
Island		
Tenerife	−0.012	−0.033
	(0.028)	(0.030)
Gran Canaria	0.001	0.031
	(0.029)	(0.031)
Other	0.029	0.010
	(0.040)	(0.054)
Nationality		
Spanish	−0.001	0.021
	(0.030)	(0.047)
EU	0.045	−0.155*
	(0.045)	(0.085)
Non-EU	−0.019	0.036
	(0.030)	(0.057)
Education		
Incomplete Primary	0.011	0.013
	(0.021)	(0.047)
Complete Primary	0.013	0.005
	(0.020)	(0.034)
Secondary Plus	−0.019	−0.013
	(0.019)	(0.036)
Mean of Dependent Variable	0.220	0.380
Observations	1,980	666

Notes: This table shows predictors of non-compliance by type. Each row corresponds to a separate regression where the dependent variable is a binary indicator of the relevant non-compliance outcome. Column 1 is estimated on the T1 and T2 subsamples jointly, with a T2 assignment dummy included to absorb differences in baseline non-compliance rates across arms; the dependent variable equals one if the participant did not collect the tablet. Column 2 is estimated on the subsample of T2 participants who collected the tablet (N = 666); the dependent variable equals one if the participant did not complete the training course. Standard errors are reported in parentheses and are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A6: Attrition between treatment groups

Treatment Group	Attrition
Intercept (control group)	0.261***
	(0.013)
T1	-0.056***
	(0.018)
T2	0.001
	(0.019)
Observations	2966

Notes: This table reports results from a regression of an attrition indicator on treatment group dummies. The dependent variable equals 1 if the individual did not participate in the follow-up survey. The intercept corresponds to the attrition rate in the control group, while the coefficients for T1 and T2 capture differences in attrition relative to the control group. Standard errors are reported in parentheses and are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A7: Selective attrition between treatment groups

Control Variable	C × Covariate	T1 × Covariate	T2 × Covariate
Female	−0.017	−0.018	−0.030
	(0.025)	(0.035)	(0.037)
Age <55	0.027	0.012	−0.034
	(0.030)	(0.037)	(0.040)
Speaks English	−0.021	0.108*	−0.037
	(0.041)	(0.065)	(0.054)
Working	0.076	−0.067	−0.114
	(0.050)	(0.065)	(0.070)
Unemployed	−0.034	−0.008	0.085
	(0.042)	(0.055)	(0.057)
Dependent in Care	−0.065*	0.141**	0.097
	(0.039)	(0.060)	(0.060)
Minor in Care	−0.060	0.117*	0.104
	(0.056)	(0.068)	(0.090)
Disability	0.030	−0.052	−0.114*
	(0.049)	(0.063)	(0.067)
Training	0.158*	−0.053	−0.164
	(0.091)	(0.119)	(0.114)
Health	0.009	0.000	−0.003
	(0.013)	(0.015)	(0.018)
Life Satisfaction	0.008	−0.014	0.009
	(0.011)	(0.014)	(0.014)
Digital Skills	−0.012	0.013	−0.011
	(0.013)	(0.020)	(0.017)
Job Search	−0.003	0.007	−0.015
	(0.012)	(0.017)	(0.022)
E-Gov Use	0.003	−0.017	−0.022
	(0.015)	(0.019)	(0.018)
PCI	−0.029	0.027	−0.018
	(0.026)	(0.039)	(0.039)
IMV	−0.010	0.004	0.031
	(0.031)	(0.048)	(0.046)

Island

Tenerife	0.019	−0.027	−0.023
	(0.026)	(0.035)	(0.038)
Gran Canaria	−0.039	0.066*	0.050
	(0.027)	(0.034)	(0.038)
Other	0.044	−0.092**	−0.063
	(0.029)	(0.045)	(0.046)
Nationality			
Spanish	−0.056*	0.064	0.088**
	(0.033)	(0.052)	(0.042)
EU	0.041	−0.093	−0.071
	(0.079)	(0.103)	(0.098)
Non-EU	0.057	−0.046	−0.087
	(0.038)	(0.057)	(0.055)
Education			
Incomplete Primary	−0.011	−0.021	−0.057
	(0.036)	(0.054)	(0.054)
Complete Primary	0.004	0.036	0.108***
	(0.027)	(0.039)	(0.041)
Secondary Plus	0.003	−0.020	−0.069**
	(0.025)	(0.039)	(0.034)
Observations		2966	

Notes: This table shows differences in attrition by treatment arm for each control variable. Three columns display the coefficients from the estimated regression equation (1). Each row corresponds to a separate regression where the dependent variable is a binary indicator of attrition, and we allow interactions between each control variable (left column) and the two treatment indicators (T1 and T2). Standard errors are reported in parentheses and are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A8: Short-Term Effects: OLS

(a) Effects on Digital Skills and Job Search

	Digital Skills		Job Search		E-Gov Use	
	(5)	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
T1	0.141**	0.179***	0.117**	0.134***	−0.009	−0.021
	(0.061)	(0.047)	(0.051)	(0.043)	(0.055)	(0.047)
T2	0.518***	0.501***	0.298***	0.273***	0.196***	0.161***
	(0.067)	(0.064)	(0.055)	(0.044)	(0.053)	(0.052)
Controls	N	Y	N	Y	N	Y
Baseline level	N	Y	N	Y	N	Y
p-value: T1 = T2	0***	0***	0.001***	0.001***	0.002***	0.001***
Mean (C)	0.101	0.101	0.040	0.040	0.230	0.230
Observations	2247	2247	2247	2247	2247	2247

(b) Effects on self-reported Employment and Life Satisfaction

	Working		Life Satisfaction	
	(1)	**(2)**	**(3)**	**(4)**
T1	0.010	0.013	0.009	0.017
	(0.019)	(0.016)	(0.060)	(0.062)
T2	−0.009	−0.008	0.118*	0.113*
	(0.016)	(0.013)	(0.065)	(0.064)
Controls	N	Y	N	Y
Baseline level	N	Y	N	Y
p-value: T1 = T2	0.322	0.195	0.063*	0.051*
Mean (C)	0.112	0.112	2.945	2.945
Observations	2247	2247	2247	2247

Notes: This table presents the results of the intervention on five key indicators: digital skills, job search ability, e-government service usage, self-reported employment, and life satisfaction. “Digital Skills”, “Job Search”, and “E-Gov Use” are composite indicators constructed from several variables in the original dataset using the method from Anderson (2008). “Job Search” captures internet-based job search behaviors, while “E-Gov Use” captures usage of e-government and essential online services. “Working” is an indicator for self-reported employment. “Life Satisfaction” is measured on a scale from 1 to 5, where 1 stands for “not satisfied at all” and 5 corresponds to “very satisfied”. The table provides two specifications for each outcome variable: one without controls and one that includes both controls and the baseline level of the outcome variable. The controls include variables such as gender, nationality, and educational level. Standard errors are in parentheses, clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A9: Medium-term effects: OLS

(a) Effects on Digital Skills and Job Search

	Digital Skills	Job Search	E-Gov Use
T1	0.178***	0.089**	−0.017
	(0.044)	(0.043)	(0.052)
T2	0.387***	0.183***	0.199***
	(0.051)	(0.044)	(0.048)
Controls	Y	Y	Y
Baseline level	Y	Y	Y
p-value: T1 = T2	0***	0.041**	0***
Mean (C)	0.073	0.129	0.237
Observations	2370	2370	2370

(b) Effects on self-reported employment and life satisfaction

	Working	Months Worked	Job Retention	Training	Life Satis-faction
T1	0.005	0.098	0.005	0.017	0.103*
	(0.016)	(0.150)	(0.081)	(0.015)	(0.057)
T2	−0.002	0.115	−0.042	0.000	0.132**
	(0.014)	(0.099)	(0.076)	(0.016)	(0.065)
Controls	Y	Y	Y	Y	Y
Baseline level	Y	Y	Y	Y	Y
p-value: T1 = T2	0.676	0.916	0.514	0.222	0.576
Mean (C)	0.117	1.317	0.689	0.096	2.876
Observations	2370	2370	231	2370	2370

Notes: This table presents the medium-term results of the intervention on several key variables, six months after the end of the intervention. Panel A reports the effects on digital skills, job search ability, and e-government service usage. “Digital Skills”, “Job Search”, and “E-Gov Use” are composite indicators constructed from several variables in the original dataset using the method from Anderson (2008), allowing us to interpret the regression coefficients in terms of standard deviations (see details in Appendix). “Job Search” captures internet-based job search behaviors, while “E-Gov Use” captures usage of e-government and essential online services. Panel B reports the effects on employment and well-being outcomes. “Working” is an indicator of self-reported employment. “Job Retention” is defined as keeping a job in the last six months since the first endline survey. “Months Worked” is the number of months an individual worked in the past year. “Life Satisfaction” is measured on a scale from 1 to 5, where 1 stands for “not satisfied at all” and 5 corresponds to “very satisfied”. All specifications control for baseline covariates and the baseline level of the outcome variable. Standard errors are in parentheses, clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A10: Medium-term Effects on Employment, Administrative Data

(a) Employment Outcomes: Social Security Regimes

Variable	**(1)** Employment	**(2)** Worked days	**(3)** Employment intensity	**(4)** General Regime	**(5)** Households Regime	**(6)** Autonomous Regime
T1	0.000	1.880	0.010	−0.005	0.003	0.000
	(0.020)	(2.711)	(0.015)	(0.020)	(0.003)	(0.004)
T2	0.022	0.578	0.003	0.025	0.000	−0.003
	(0.017)	(2.228)	(0.012)	(0.015)	(0.002)	(0.004)
Controls	Y	Y	Y	Y	Y	Y
Baseline level	Y	Y	Y	Y	Y	Y
p-value: T1 = T2	0.215	0.623	0.623	0.096*	0.341	0.076*
Mean (C)	0.184	23.643	0.128	0.161	0.010	0.010
Observations	2175	2175	2175	2175	2175	2175

(b) Employment Outcomes: Contract Types

Variable	Permanent contract	Discontinued perma-nent contract	Temporal contract	Full-time contract	Part-time contract
T1	−0.010	0.001	0.011	−0.004	0.006
	(0.011)	(0.005)	(0.017)	(0.015)	(0.013)
T2	−0.003	0.009*	0.020	0.014	0.012
	(0.012)	(0.005)	(0.013)	(0.015)	(0.013)
Controls	Y	Y	Y	Y	Y
Baseline level	Y	Y	Y	Y	Y
p-value: T1 = T2	0.483	0.154	0.604	0.192	0.648
Mean (C)	0.082	0.012	0.072	0.070	0.096
Observations	2175	2175	2175	2175	2175

Notes: These tables present the medium-term effects of the intervention on employment outcomes using administrative data from Social Security records. Panel A reports effects on subsequent employment, number of worked days, employment intensity, and participation in different social security regimes (General, Household, and Self-employed). Panel B continues with contract characteristics, including permanent, discontinuous permanent, temporary, full-time, and part-time contracts. Each column reports results from an OLS regression of the outcome on treatment assignment indicators, controlling for baseline covariates such as gender, nationality, and educational level, as well as the baseline value of the dependent variable. Standard errors are reported in parentheses and are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A11: Lee (2009) Bounding Method for the Effects on Key Outcomes

Variable	T1 – C: Raw means	T1 – C: Lower bound	T1 – C: Upper bound	T2 – C: Raw means	T2 – C: Lower bound	T2 – C: Upper bound
Digital Skills	0.141	−0.064	0.284	0.518	0.512	0.531
Job Search	0.117	−0.015	0.222	0.298	0.296	0.300
E-Gov Use	−0.009	−0.208	0.076	0.196	0.193	0.203
Working	0.010	−0.056	0.019	−0.009	−0.009	−0.007
Life Satisfaction	0.009	−0.145	0.156	0.118	0.115	0.121

Notes: This table presents Lee (2009) bounds for the short-term effects of the intervention on digital skills, job search ability, e-government use, self-reported employment, and life satisfaction. "Digital Skills", "Job Search", and "E-Gov Use" are composite indicators constructed using the method from Anderson (2008). "Working" is an indicator for self-reported employment. "Life Satisfaction" is measured on a scale from 1 to 5, where 1 stands for "not satisfied at all" and 5 corresponds to "very satisfied". The raw means difference is reported alongside the lower and upper bounds, which are obtained by trimming the sample to account for differential attrition across treatment arms.

Table A12: Short-Term Effects: IV

	Digital Skills	Job Search	E-Gov Use	Working	Life Satis-faction
T1	0.191***	0.143***	−0.023	0.014	0.018
	(0.050)	(0.046)	(0.050)	(0.018)	(0.066)
T2	0.885***	0.466***	0.324***	−0.022	0.211**
	(0.104)	(0.072)	(0.093)	(0.023)	(0.105)
Controls	Y	Y	Y	Y	Y
Baseline level	Y	Y	Y	Y	Y
p-value: T1 = T2	0***	0***	0***	0.190	0.031**
Mean (C)	0.101	0.040	0.230	0.112	2.945
Observations	2247	2247	2247	2247	2247

Notes: This table presents the results of the intervention on digital skills, job search ability, self-reported employment and life satisfaction using IV estimation. "Digital Skills" and "Job Search" are composite indicators constructed from several variables in the original dataset, using the method from Anderson (2008). "Working" is an indicator for self-reported employment. "Life Satisfaction" is measured on a scale from 1 to 5, where 1 stands for "not satisfied at all" and 5 corresponds to "very satisfied". Each column provides results of an IV regression, where treatment assignment was used as an instrument for the treatment compliance. The controls include variables such as gender, nationality, and educational level. Standard errors are put in parentheses, clustered at the node level. *: $p<0.1$, **: $p<0.05$, ***: $p<0.01$.

Table A13: Medium-term effects: IV

(a) Effects on Digital Skills and Job Search

	Digital Skills (IV)	Job Search (IV)	E-Gov Use (IV)
T1	0.192***	0.096**	−0.019
	(0.048)	(0.047)	(0.056)
T2	0.699***	0.327***	0.422***
	(0.086)	(0.079)	(0.087)
Controls	Y	Y	Y
Baseline level	Y	Y	Y
p-value: T1 = T2	0***	0.006***	0***
Mean (C)	0.073	0.129	0.237
Observations	2370	2370	2370

(b) Effects on self-reported employment and life satisfaction

	Working (IV)	Months Worked (IV)	Job Retention (IV)	Training (IV)	Life Satisfaction (IV)
T1	0.005	0.107	0.004	0.018	0.112*
	(0.017)	(0.162)	(0.086)	(0.017)	(0.062)
T2	−0.007	0.181	−0.125	−0.009	0.214*
	(0.026)	(0.199)	(0.185)	(0.028)	(0.115)
Controls	Y	Y	Y	Y	Y
Baseline level	Y	Y	Y	Y	Y
p-value: T1 = T2	0.687	0.785	0.452	0.297	0.312
Mean (C)	0.117	1.317	0.689	0.096	2.876
Observations	2370	2370	231	2370	2370

Notes: This table presents the medium-term results of the intervention on several key variables, six months after the end of the intervention. Panel A reports the effects on digital skills and job search abilities. Each of these composite indicators is constructed from several variables in the original dataset, using the method from Anderson (2008), allowing us to interpret the regression coefficients in terms of standard deviations (see details in Appendix). Panel B reports the effects on self-reported employment and life satisfaction. "Working" is an indicator for self-reported employment. "Job Retention" is defined as keeping a job in the last six months, since the first endline survey. "Months Worked" is the number of months an individual worked in the past year. "Life Satisfaction" is measured on a scale from 1 to 5, where 1 stands for "not satisfied at all" and 5 corresponds to "very satisfied". Each column provides results of an IV regression, where treatment assignment was used as an instrument for the treatment compliance. The controls include baseline level of the outcome and variables such as gender, nationality, and educational level. Standard errors are provided in parentheses, clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A14: Heterogeneous Effects by Gender (medium-term effects)

	Working	Months Worked	Job Retention	Digital Skills	Job Search	Training	Life Satisfaction	E-Gov Use
T1	0.000	0.007	−0.297*	0.167**	0.097	−0.004	0.222***	−0.058
	(0.028)	(0.237)	(0.154)	(0.077)	(0.074)	(0.029)	(0.085)	(0.083)
Female×T1	0.009	0.135	0.376**	0.010	−0.021	0.030	−0.188	0.060
	(0.032)	(0.255)	(0.167)	(0.102)	(0.086)	(0.032)	(0.121)	(0.105)
T2	−0.026	0.036	−0.375*	0.378***	0.234***	−0.039	0.255***	0.164
	(0.023)	(0.168)	(0.201)	(0.080)	(0.085)	(0.028)	(0.095)	(0.112)
Female×T2	0.037	0.124	0.420*	0.004	−0.082	0.059*	−0.182	0.043
	(0.024)	(0.220)	(0.219)	(0.094)	(0.105)	(0.035)	(0.126)	(0.133)
Mean (C)	0.117	1.317	0.689	0.073	0.129	0.096	2.876	0.237
Obs.	2370	2370	231	2370	2370	2370	2370	2370

Notes: This table reports the intervention effects on eight key outcomes, stratified by gender. We extend our preferred specifications from Table A9 (with full controls and baseline outcome values) by including a dummy variable for female participants, and its interaction with the treatment dummies (T1 and T2). "Working" is an indicator for self-reported employment, and "Life Satisfaction" is on a 1–5 scale. "Digital Skills", "Job Search", and "E-Gov Use" are standardized composite indicators (following Anderson 2008), with coefficients interpreted in standard deviations (see Appendix for details). "Job Retention" is defined as keeping a job in the last six months, since the first endline survey. "Months Worked" is the number of months an individual worked in the past year. Standard errors (in parentheses) are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A15: Heterogeneous Effects by Dependent or Minor in Care (short-term effects)

	Working	Digital Skills	Job Search	Life Satisfaction	E-Gov Use
T1	0.014	0.140***	0.120**	0.037	−0.047
	(0.018)	(0.051)	(0.048)	(0.068)	(0.050)
Dependent×T1	−0.006	0.243	0.121	−0.087	0.196
	(0.044)	(0.148)	(0.123)	(0.165)	(0.120)
T2	−0.014	0.450***	0.267***	0.142**	0.142***
	(0.013)	(0.068)	(0.045)	(0.069)	(0.054)
Dependent×T2	0.043	0.322**	0.043	−0.198	0.159
	(0.039)	(0.144)	(0.126)	(0.158)	(0.145)
Mean (C)	0.112	0.101	0.040	2.945	0.230
Obs.	2247	2247	2247	2247	2247

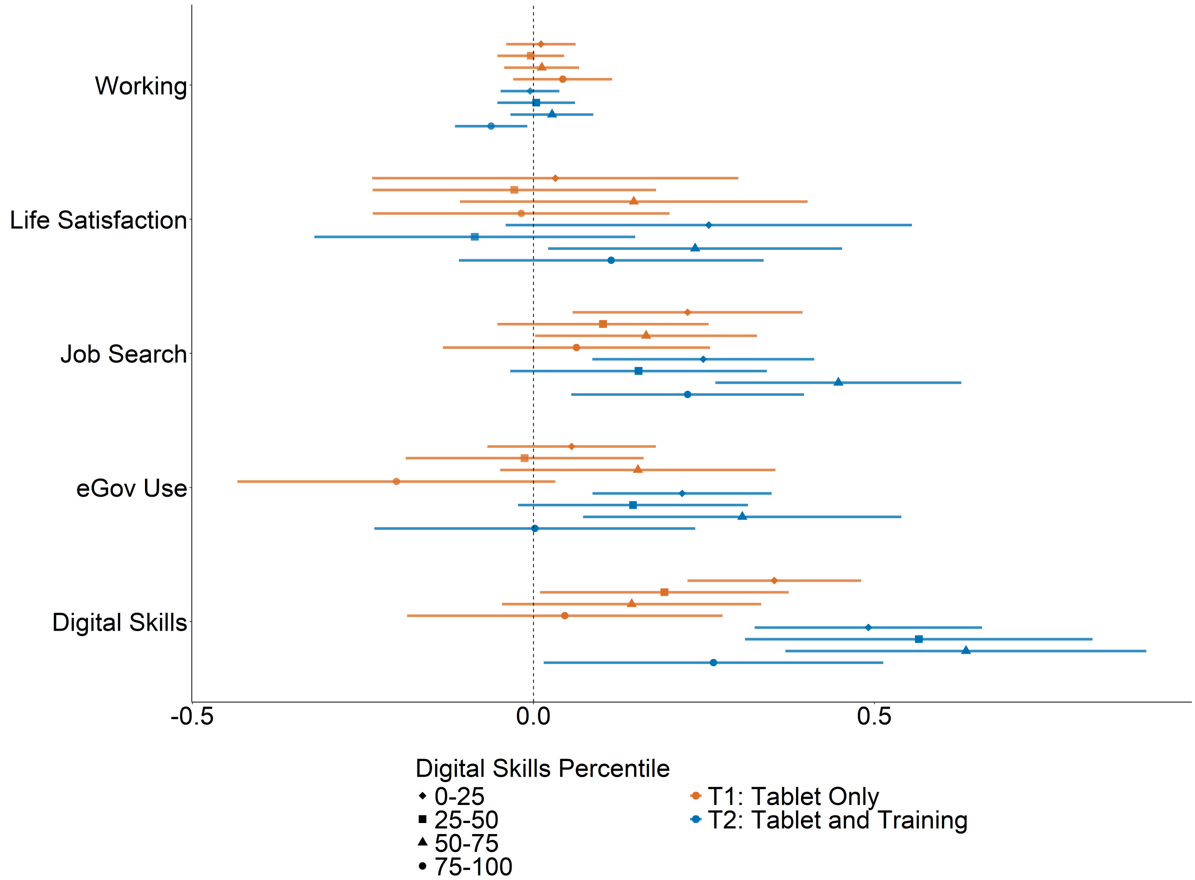
Notes: This table reports the intervention effects on five key outcomes, stratified by having a dependent in care. We extend our preferred specifications from Table A8 (with full controls and baseline outcome values) by including a dummy variable for having a dependent or minor in care, and its interaction with the treatment dummies (T1 and T2). "Working" is an indicator for self-reported employment, and "Life Satisfaction" is on a 1–5 scale. "Digital Skills", "Job Search", and "E-Gov Use" are standardized composite indicators (following Anderson 2008), with coefficients interpreted in standard deviations (see Appendix for details). Standard errors (in parentheses) are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A16: Heterogeneous Effects by Dependent or Minor in Care (medium-term effects)

	Working	Months Worked	Job Retention	Digital Skills	Job Search	Training	Life Satisfaction	E-Gov Use
T1	0.002	0.145	0.031	0.191***	0.097**	0.012	0.121**	−0.039
	(0.017)	(0.157)	(0.097)	(0.047)	(0.048)	(0.016)	(0.055)	(0.057)
Dependent×T1	0.020	−0.430	−0.397**	−0.082	−0.055	0.026	−0.157	0.119
	(0.038)	(0.332)	(0.179)	(0.091)	(0.127)	(0.040)	(0.135)	(0.135)
T2	−0.013	0.041	−0.045	0.375***	0.168***	0.000	0.118*	0.168***
	(0.014)	(0.113)	(0.091)	(0.055)	(0.049)	(0.018)	(0.069)	(0.052)
Dependent×T2	0.085**	0.576	0.031	0.109	0.130	−0.001	0.115	0.175
	(0.043)	(0.407)	(0.148)	(0.107)	(0.130)	(0.040)	(0.182)	(0.162)
Mean (C)	0.117	1.317	0.689	0.073	0.129	0.096	2.876	0.237
Obs.	2370	2370	231	2370	2370	2370	2370	2370

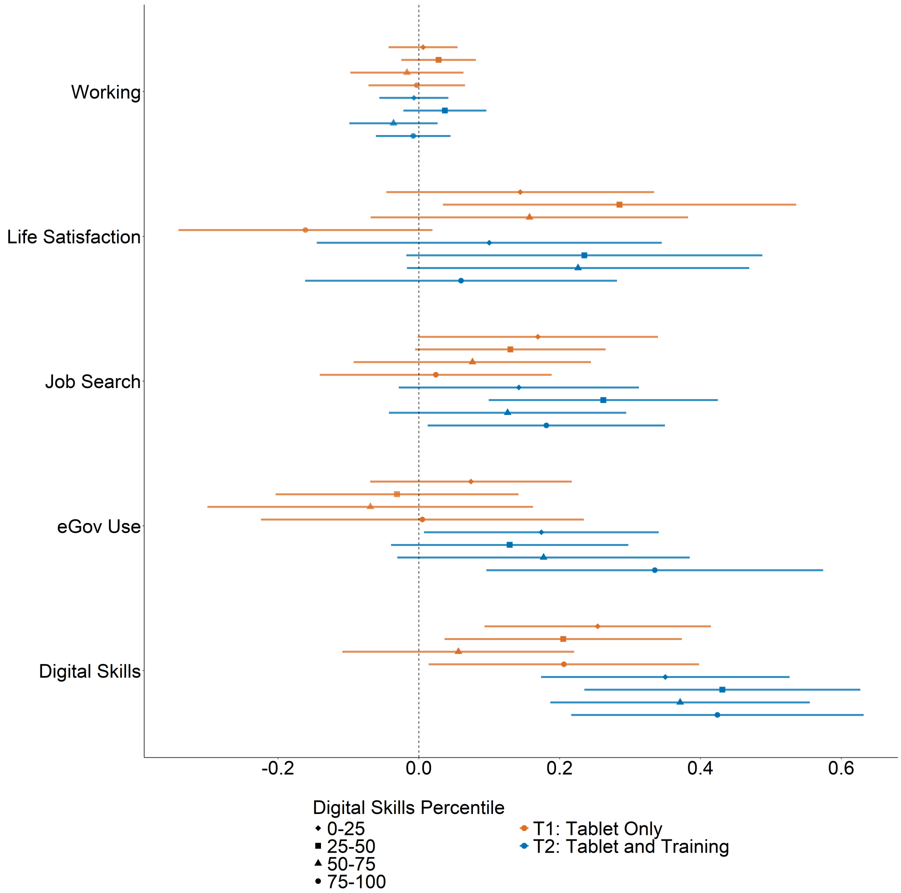
Notes: This table reports the intervention effects on eight key outcomes, stratified by having a dependent in care. We extend our preferred specifications from Table A9 (with full controls and baseline outcome values) by including a dummy variable for having a dependent or minor in care, and its interaction with the treatment dummies (T1 and T2). "Working" is an indicator for self-reported employment, and "Life Satisfaction" is on a 1–5 scale. "Digital Skills", "Job Search", and "E-Gov Use" are standardized composite indicators (following Anderson 2008), with coefficients interpreted in standard deviations (see Appendix for details). "Job Retention" is defined as keeping a job in the last six months, since the first endline survey. "Months Worked" is the number of months an individual worked in the past year. Standard errors (in parentheses) are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Figure A1: Heterogeneity Plot for Short-Term Effects (Digital Skills)



Notes: This graph shows how treatment effects vary by the baseline level of digital skills. Blue points (Treatment 2: Digital Training + Tablet) and orange points (Treatment 1: Tablet only) indicate the effect sizes. The shapes represent different quartiles: diamond for the 0-25 percentile, square for the 25-50 percentile, triangle for the 50-75 percentile, and circle for the 75-100 percentile. Horizontal lines denote 95% confidence intervals.

Figure A2: Heterogeneity Plot for Medium-Term Effects (Digital Skills)



Notes: This graph shows how treatment effects vary by the baseline level of digital skills. Blue points (Treatment 2: Digital Training + Tablet) and orange points (Treatment 1: Tablet only) indicate the effect sizes. The shapes represent different quartiles: diamond for the 0-25 percentile, square for the 25-50 percentile, triangle for the 50-75 percentile, and circle for the 75-100 percentile. Horizontal lines denote 95% confidence intervals.

B Variables Definition

This section describes in detail all the variables used in the analysis, which appear in descriptive statistics, balance test and/or used as variables of interest or controls in the regression analysis.

B.1 Variables

- **Female** – a binary variable which is equal to 1 if a person responds "Woman" to Question 2 ("Sex")
- **Age <55** – a binary variable which is equal to 1 if a person responds "From 45 to 54 years old" to Question 3
- **Speaks English** – a binary variable which is equal to 1 if a person responds "English" to Question 8 ("Which languages do you speak, besides Spanish?")
- **Working** – a binary variable which is equal to 1 if a person responds "Working" to Question 9 ("What is your occupational situation?")
- **Unemployed** – a binary variable which is equal to 1 if a person responds "Unemployed and actively seeking work" to Question 9 ("What is your occupational situation?")
- **Dependent in Care** – a binary variable which is equal to 1 if a person responds "Yes" to Question 11 ("Are you responsible for the care of a dependent person or a minor not in school?"), subsection "Dependent person"
- **Minor in Care** – a binary variable which is equal to 1 if a person responds "Yes" to Question 11 ("Are you responsible for the care of a dependent person or a minor not in school?"), subsection "Minor"
- **Disability** – a binary variable which is equal to 1 if a person responds "Yes, physical disability" to Question 12 ("Do you have a disability greater than 33
- **Training** – a binary variable which is equal to 1 if a person responds "Yes" to Question 15 ("In the last 6 months, did you do any training for employment?")
- **Months Worked** – a discrete variable ranging from 0 to 12 which corresponds to the answer to Question 48 of the second endline survey ("In the last year, during how many months did you work?")
- **Health** – a discrete variable ranging from 1 to 5 which corresponds to the answer to Question 41 ("Finally, rate from 1 to 5, where 1 is very bad and 5 is very good, your health status in the last three months")
- **Life Satisfaction** – a discrete variable ranging from 1 to 5 which corresponds to the answer to Question 42 ("Lastly, rate from 1 to 5, where 1 is very little and 5 is a lot, how satisfied do you feel with your life in general in the last 3 months?")

- **PCI** – a binary variable which is equal to 1 if a person responds “PCI” or “Both” to Question 4 (“Do you receive the Minimum Vital Income (IMV), the Canary Insertion Benefit (PCI), or both?”)

- **IMV** – a binary variable which is equal to 1 if a person responds “IMV” or “Both” to Question 4 (“Do you receive the Minimum Vital Income (IMV), the Canary Insertion Benefit (PCI), or both?”)

- **Island** - a categorical variable with values Gran Canaria, Tenerife and Other (includes Lanzarote, Fuenteventura and La Palma). Corresponds to the answer to Question 5 (“On which island do you live?”). Observations with values La Gomera, El Hierro and La Graciosa are dropped from the original dataset.

- **Education** – a categorical variable with values Incomplete Primary, Complete Primary, and Secondary Studies. Corresponds to the answer to Question 13 (“What is your highest level of education?”).

- **Nationality** - a categorical variable with values Spanish, EU and Non-EU. Corresponds to the answer to Question 7 (“What is your nationality?”).

B.2 Composite Indicators

Each composite indicator is constructed from several variables in the original dataset, using the method from Anderson (2008). Specifically, we normalize to mean 0 and standard deviation 1 in the baseline dataset; then each variable is standardized by subtracting its baseline means and dividing by its baseline standard deviation, then we take their weighted sum, where weights are proportional to sums of rows in the inverse covariance matrix of standardized variables at baseline.
Digital Skills: an indicator showing how confident respondents feel in their skills of using the internet and electronic devices. We used answers to the following questions in order to create this indicator:

- **Question 28**: “Regarding the digital world, do you consider that you know more, the same, or less than most people around you?” Answers “Knows more than most people” and “Knows the same as most people” are pooled together and correspond to 1 in the original variable, answer “Knows less than most people” corresponds to 0 in the original variable.

- **Question 29**: “Next, rate the following items from 1 to 5, where 1 is none and 5 is a lot”. 4 variables, corresponding to self-reported answers to the following subsections, were used: “How much digital knowledge and skills do you consider you have?”, “How easy is it for you to browse the Internet?”, “How much interest do you have in digital and internet topics?”, and “How much confidence do you have in the internet?”.

- **Question 30**: “In the last 3 months, which of the following computer-related tasks have you performed?”. 11 binary variables, corresponding to 1 if a person responds “Yes” to the following list of questions, were used: “Copy or move files or folders”, “Use Word or another word processor”, “Use Excel or other spreadsheets”, “Use advanced Excel functions — functions, formulas, macros, Visual Basic, etc.”, "Create documents, images, videos, etc. that incorporate various elements, e.g., text, tables, graphics, animation", "Use programs or software to edit photos, video or audio", "Change the settings of the computer, mobile phone, tablet, etc., e.g., adjust language, colors, text size, toolbar/menu, or solve a basic computer problem, completely erase a hard drive, folders or files by mistake", "Set up the internet connection or solve browsing problems", "Program in a programming language".

- **Question 31**: "Answer the following statements with yes, no, or not sure. In the last three months...". 7 binary variables, corresponding to 1 if a person responds "Yes" to the following list of questions, were used: "Your digital knowledge has helped you learn new things", "You have been able to solve a technical problem that you couldn't before", "You have needed less help to use the internet, mobile, computer, or other electronic device", "You dare to do more things on your own without asking for help", "You have taught another person to use the internet, mobile, computer, or another electronic device", "You have shared what you know through forums or social networks", "You have learned something new by watching videos, reading forums, or through apps or websites".

- **Question 32**: "And now, from the following tasks related to your smartphone and/or tablet, tell me which ones you have done in the last 3 months". 7 binary variables, corresponding to 1 if a person responds "Yes" to the following list of questions, were used: "Receive or send emails", "Use Whatsapp, Telegram, etc. — instant messaging", "Use apps and platforms for videoconferencing — e.g., Zoom, Jitsi Meet", "Take photos and/or record audios or videos", "Upload photos, videos, etc. to social media", "Change the settings of the mobile or of installed apps/programs", "Download or install apps or programs".

E-Gov Use: an indicator showing how often people use the internet to access electronic government services. We used answers to the following questions in order to create this indicator:

- **Question 21A**: "Now tell me if you have done the following things I am going to read". 10 binary variables, corresponding to 1 if a person confirms that she has used Internet for the following actions in the last 3 months, were used: "Book an appointment with the doctor or nurse at your health center", "Access your medical record", "Renew unemployment benefits", "Request your work history certificate", "Search for information on public administration websites or apps", "Download or print official forms", "Send forms online, e.g., tax return, taxes, renew ID, register address, etc.", "Receive an SMS with a link to download documents", "Chat with a support person", "Other"

- **Question 22**: "Now tell me if in the last 3 months you have done any of the following things related to essential services such as water, energy, transport, etc.". 6 binary variables, corresponding to 1 if a person confirms that she has used Internet for the following actions in the last 3 months, were used: "Use online banking", "Receive digital bills", "Manage water, electricity, internet contracts, etc.", "Request the electricity subsidy", "Request the social water tariff", "Request the resident subsidy".

Job Search: an indicator showing how often people use the internet to search for jobs online. We used answers to the following questions in order to create this indicator:

- **Question 35**: "In the last 3 months, have you used the internet to look for a job or send a job application?" A binary variable, which is equal to 1 if a person responds "Yes", is used.

- **Question 38**: "In the last 3 months, have you searched for information on courses to improve your professional profile or taken an online course to improve your employability?". A binary variable, which is equal to 1 if a person responds "Yes", is used.

- **Question 39**: "Do you use online job portals?". A binary variable, which is equal to 1 if a person responds "Yes", is used.

- **Question 40**: "In your curriculum vitae, are you able to clearly reflect your professional and personal skills?". A binary variable, which is equal to 1 if a person responds "Yes", is used.

Online Appendix

For web publication only

C Heterogeneous Treatment Effects

To gain deeper insights into the intervention's impact across different social groups, we conducted a heterogeneity analysis. Following our pre-analysis plan, we first explored heterogeneous effects by gender to understand whether men and women benefited differently from the interventions (Figures C1 and C2). In the short term, the impacts of both T1 and T2 on core outcomes such as digital skills, job search capabilities, and life satisfaction were largely homogeneous, with no statistically significant differences between men and women. However, in the medium term, notable gender differences emerged regarding labor market attachment and continued skill development (see Table A14). Specifically, women in both treatment groups (T1 and T2) exhibited significantly higher job retention rates compared to men six months post-intervention. Furthermore, women who received both the tablet and training (T2) showed a higher likelihood of participating in subsequent job training compared to their male counterparts. These findings suggest that while initial digital skill acquisition is similar across genders, women may be more effective at leveraging these digital inclusion interventions to maintain employment and proactively pursue further professional development over time. This could reflect different importance of digital-skills across occupation; like occupations that tend to be more female-dominated.

In addition to this pre-specified analysis, we conducted several exploratory heterogeneity analyses to evaluate other potential mechanisms. First, we hypothesized that participants' education levels might influence how they benefit from the provision of tablets and digital literacy training. The direction of this effect depends on whether the training complements or substitutes for formal education: on one hand, individuals with more education might benefit more because they can better process new information; on the other, those with less education might gain disproportionately by acquiring skills they previously lacked.

To examine these hypotheses, we extended our preferred specifications, which include a full set of controls and the baseline outcome level, by adding dummy variables for education levels and interacting them with the treatment indicators (T1 and T2), as well as the standard set of controls. We categorized education into three groups: incomplete primary (no formal education or partial primary completion), complete primary (completed primary but dropped out of subsequent levels), and secondary (ranging from incomplete secondary to started high school without graduating). The results, illustrated in Figures

C3-C4, do not show any significant effects on employment status, e-government use, or life satisfaction across the education levels (see Tables C2-C3 for further details). However, for digital skills, participants in T2 with complete primary education showed the largest short-term improvement, about 0.57 standard deviations, compared to 0.1 for the control mean, although the null hypothesis of homogeneous effects across subgroups cannot be rejected. For job search capabilities, the subgroup with complete primary education exhibited the most substantial gains. In the medium term, the largest improvements in both digital skills and job search capabilities were observed among participants with secondary education. Similarly, T1 also generated gains in digital skills, with the highest short-term effect occurring among those with incomplete primary education and the highest medium-term effect among those with secondary education. One plausible explanation is that even a modest educational foundation can help individuals better absorb and retain new information over time.

We also examined heterogeneity based on participants' initial (pre-intervention) digital skills, which we divided into quartiles. We created dummy variables for each quartile and interacted them with the treatment indicators and other controls in OLS regressions using the same outcomes as before. As shown in Figures A1-A2, T1 participants with the lowest baseline digital skills registered significantly larger short-term improvements in self-reported endline digital skills compared to higher quartiles (see Tables C4-C5 for further details). This suggests that providing access to digital devices is especially beneficial for those with limited initial digital literacy, enabling them to acquire basic digital skills independently.

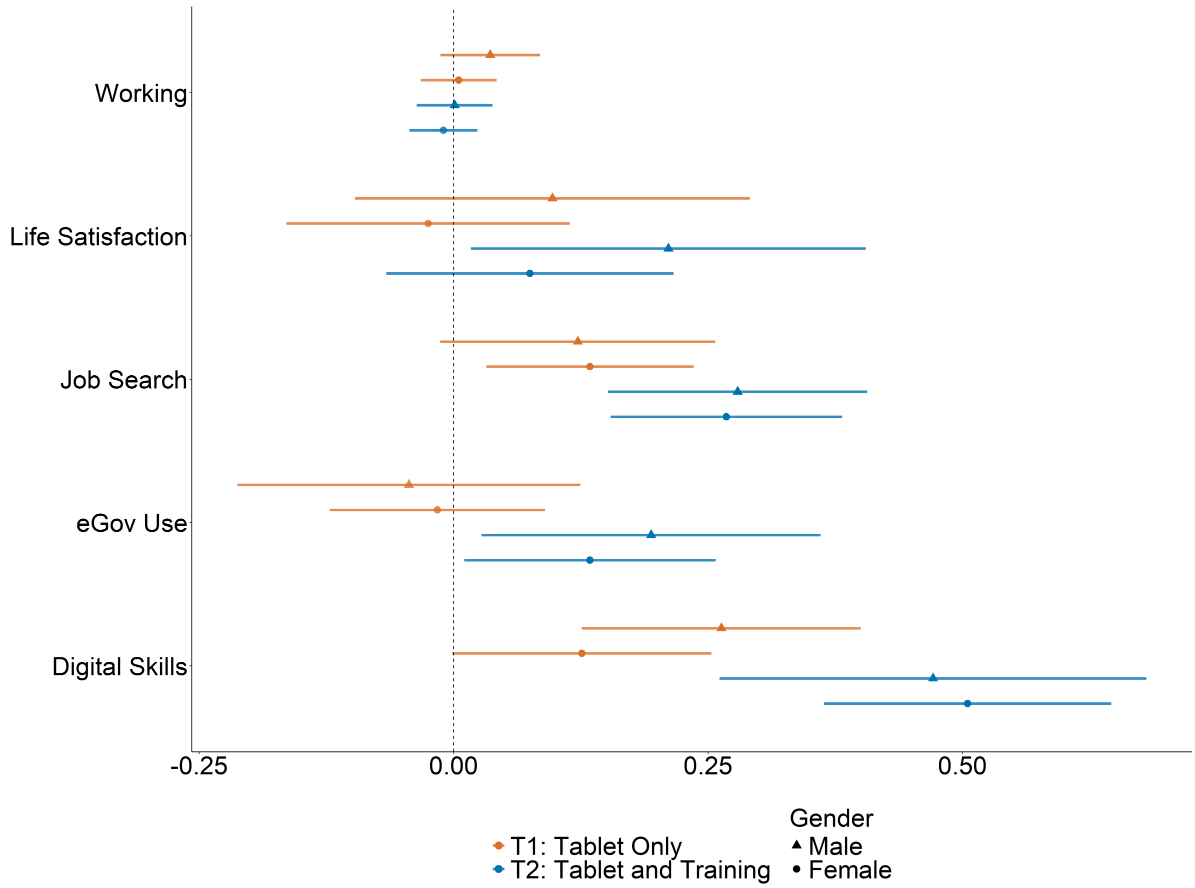
To explore the heterogeneity by the potential selective attrition, we analyzed heterogeneity based on two characteristics that either differed between treatment arms at baseline or were linked to selective attrition: enrollment in the Canarian Insertion Benefit (PCI) and having a dependent.[13] As shown in Tables C6–A16 and Figures C5–C8, PCI enrollment does not significantly moderate any treatment effects in the short term. In the medium term, T2's effect on job retention and months of employment was significantly lower for those enrolled in PCI, possibly reflecting reduced incentives among individuals receiving substantial unemployment benefits. Moreover, participants with a dependent—whether adult or minor—experienced larger short-term gains in digital skills from T2 than those without dependents. In the medium term, T2 participants with dependents were also more likely to be working, though T1 participants with dependents showed significantly

[13] We combined dummies for having an adult dependent and for having a dependent or minor in care into a single variable, which we then interacted with the treatment indicators.

lower job retention, presenting a more nuanced picture of how caregiving responsibilities interact with treatment effects.

Overall, these analyses reveal that treatment effects vary mildly across different subpopulations. Future research could employ more data-driven methods to systematically explore additional sources of heterogeneity beyond the exploratory dimensions examined here.[14]

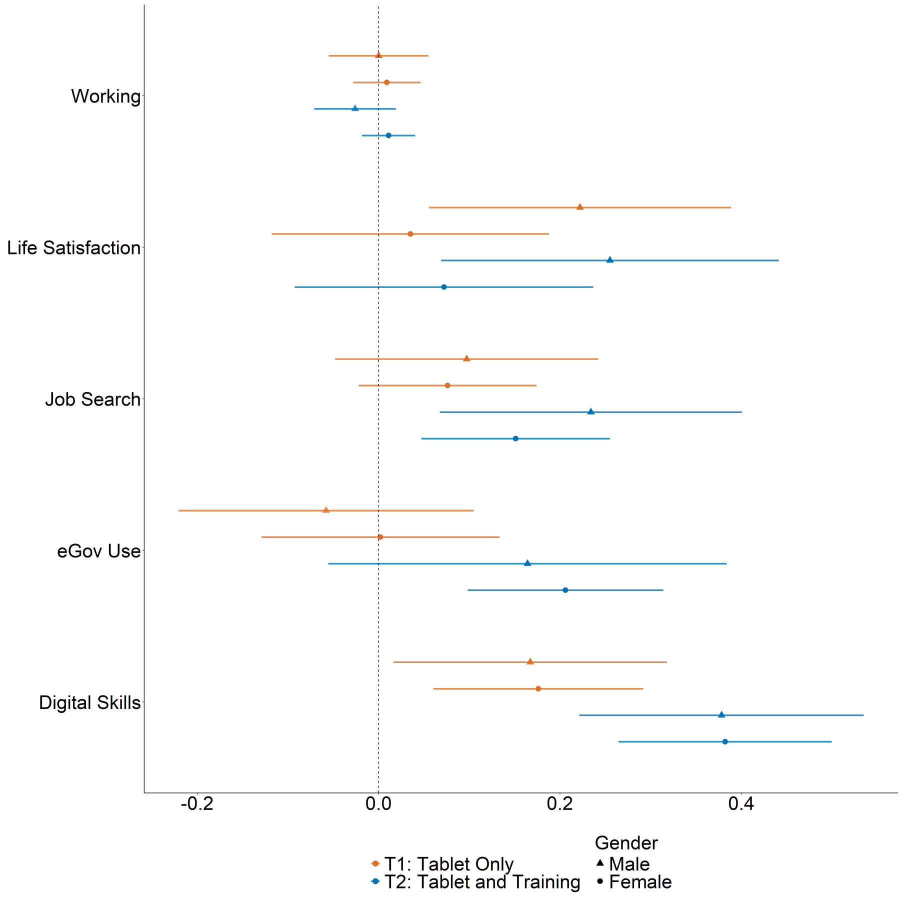
Figure C1: Heterogeneity Plot for Short-Term Effects (Gender)



Notes: This graph shows how treatment effects vary by gender. Blue points (Treatment 2: Digital Training + Tablet) and orange points (Treatment 1: Tablet only) indicate the effect sizes. The shapes represent gender: triangle for male, and circle for female. Horizontal lines denote 95% confidence intervals.

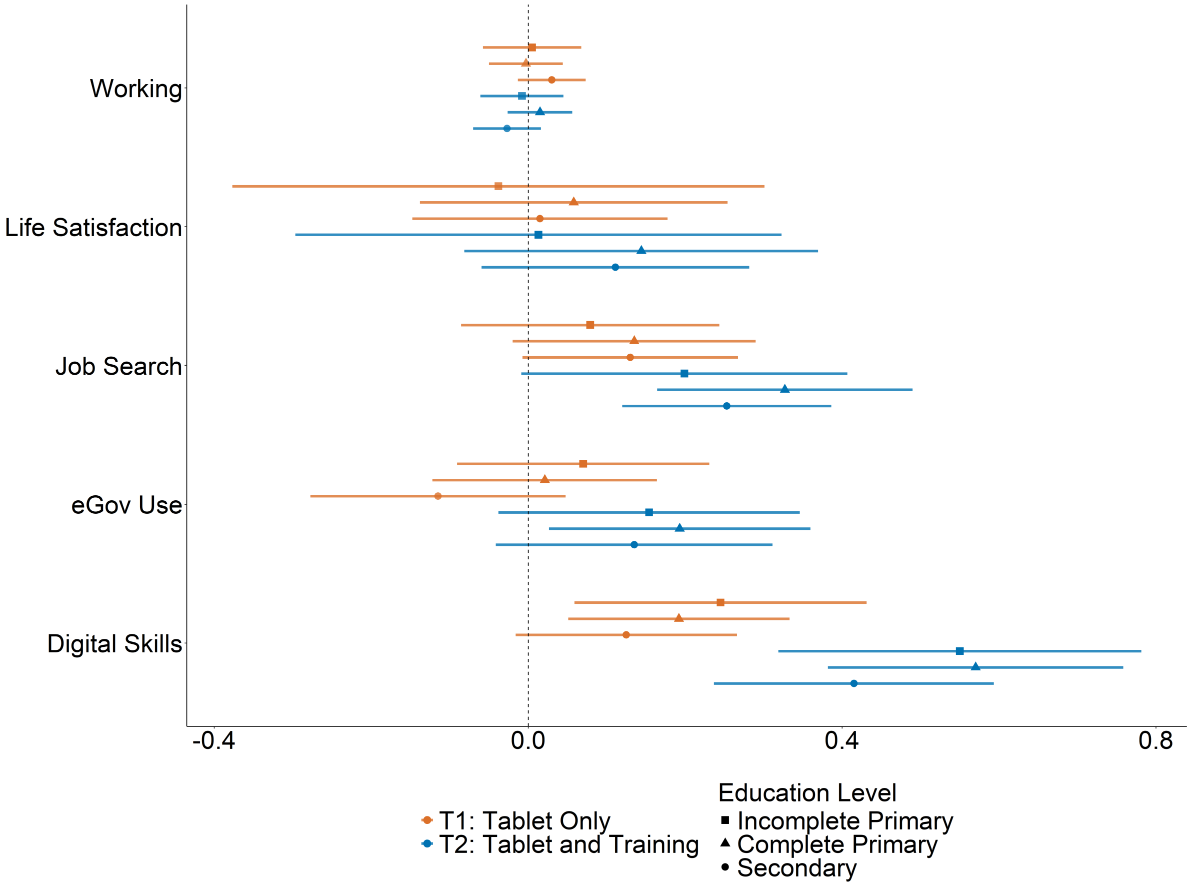
[14]Heterogeneity analyses by PCI and dependent status, in particular, were motivated by baseline imbalances and patterns of selective attrition. Therefore, these exploratory analyses were not prespecified and may involve multiple-testing concerns. Nevertheless, we report them as exploratory, without formal corrections, and focus on patterns consistent across outcomes. Main intervention effects on digital skills and job search remain large and robust.

Figure C2: Heterogeneity Plot for Medium-Term Effects (Gender)



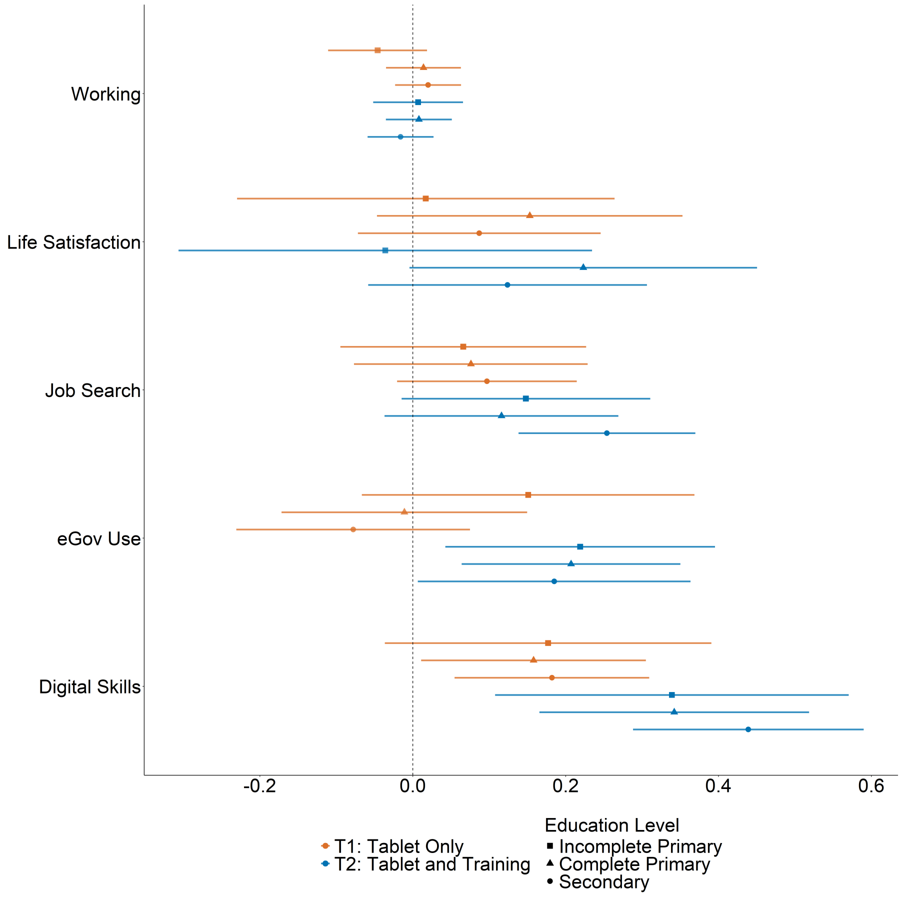
Notes: This graph shows how treatment effects vary by gender. Blue points (Treatment 2: Digital Training + Tablet) and orange points (Treatment 1: Tablet only) indicate the effect sizes. The shapes represent gender: triangle for male, and circle for female. Horizontal lines denote 95% confidence intervals.

Figure C3: Heterogeneity Plot for Short-Term Effects (Education)



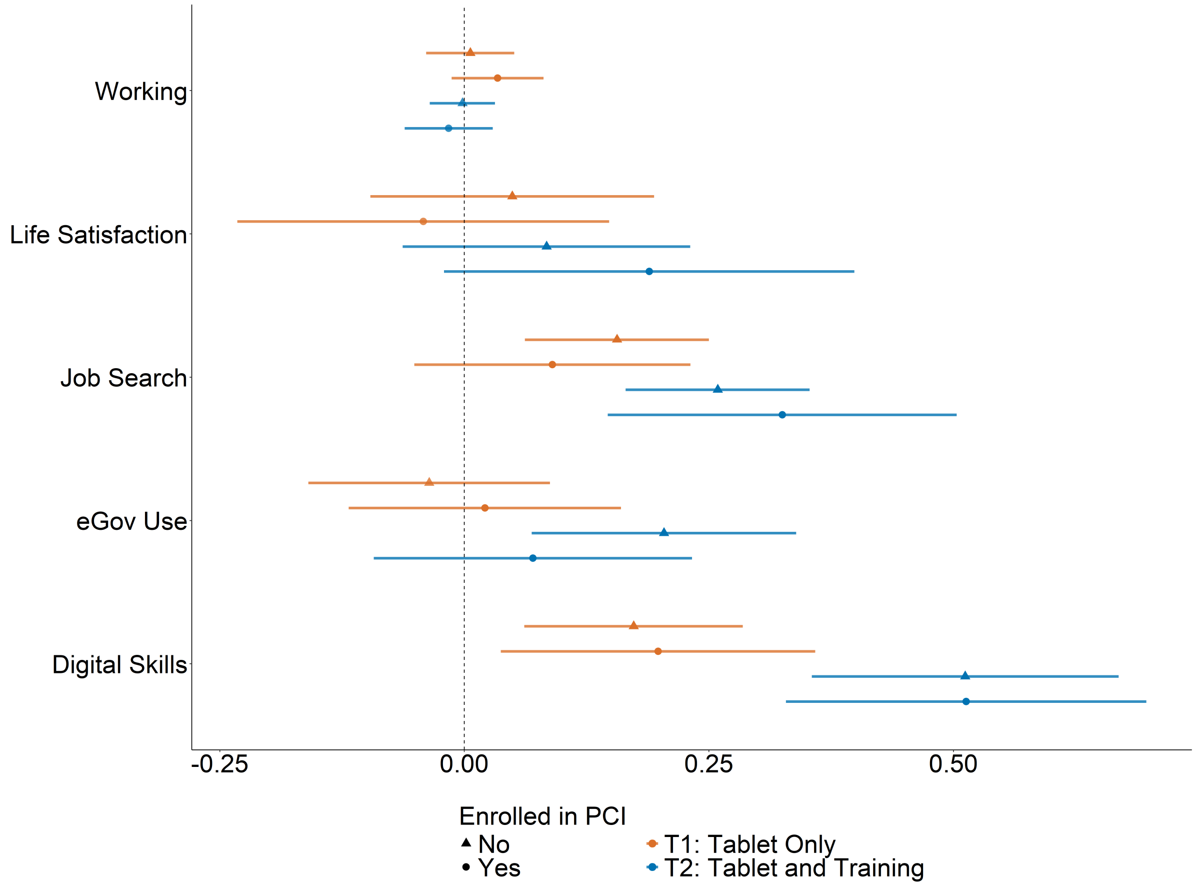
Notes: This graph shows how treatment effects vary by education level. Blue points (Treatment 2: Digital Training + Tablet) and orange points (Treatment 1: Tablet only) indicate the effect sizes. The shapes represent education levels: squares for those without complete primary education, triangles for those with complete primary education, and circles for those who started secondary education. Horizontal lines denote 95% confidence intervals.

Figure C4: Heterogeneity Plot for Medium-Term Effects (Education)



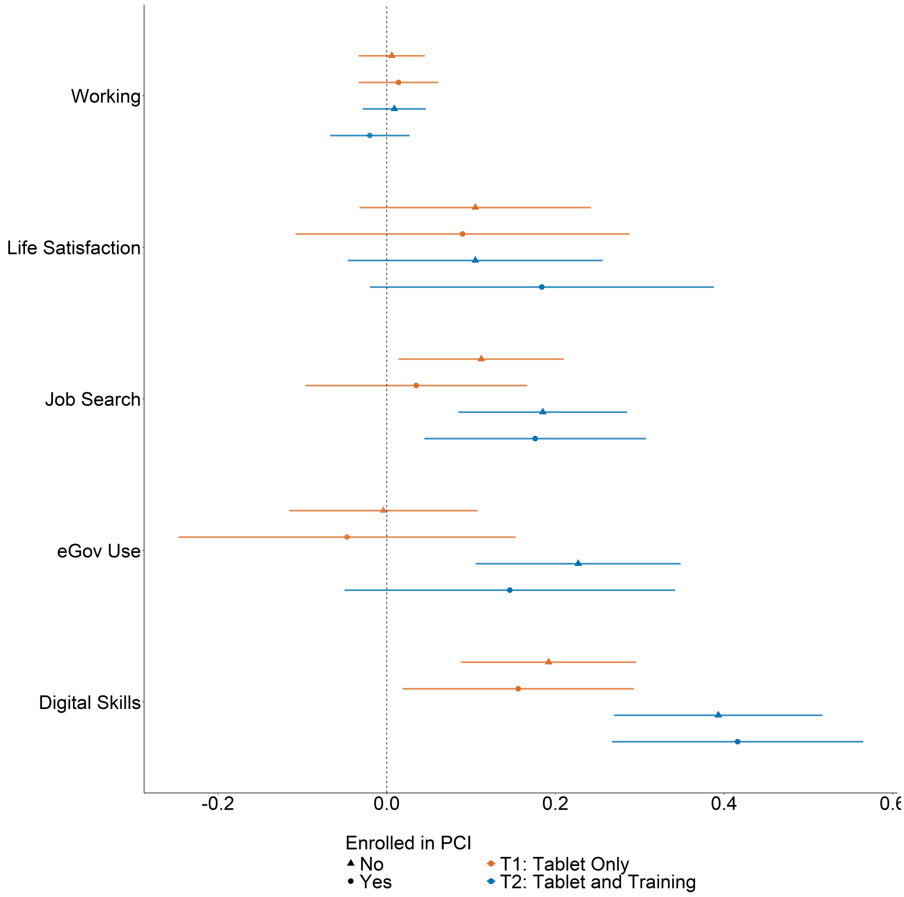
Notes: This graph shows how treatment effects vary by education level. Blue points (Treatment 2: Digital Training + Tablet) and orange points (Treatment 1: Tablet only) indicate the effect sizes. The shapes represent education levels: squares for those without complete primary education, triangles for those with complete primary education, and circles for those who started secondary education. Horizontal lines denote 95% confidence intervals.

Figure C5: Heterogeneity Plot for Short-Term Effects (PCI)



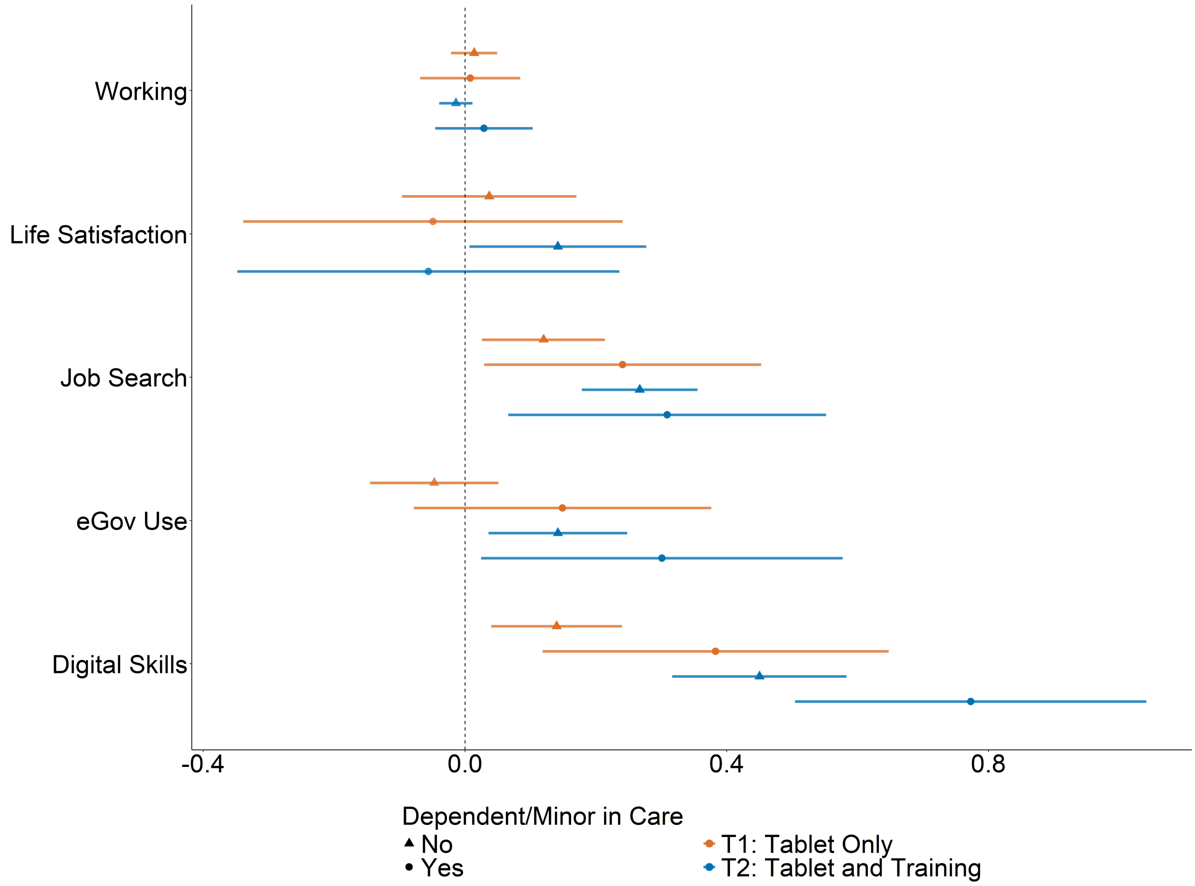
Notes: This graph shows how treatment effects vary by PCI enrollment. Blue points (Treatment 2: Digital Training + Tablet) and orange points (Treatment 1: Tablet only) indicate the effect sizes. The shapes represent the status of enrollment in PCI: triangle for not being enrolled, and circle for being enrolled. Horizontal lines denote 95% confidence intervals.

Figure C6: Heterogeneity Plot for Medium-Term Effects (PCI)



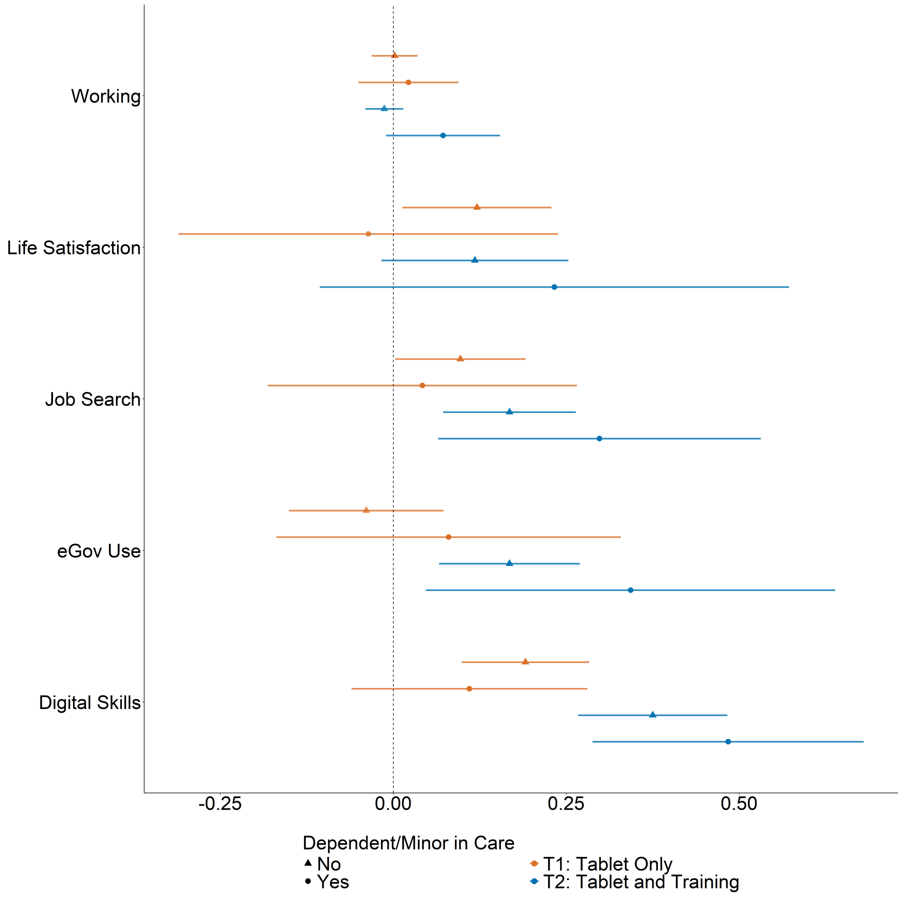
Notes: This graph shows how treatment effects vary by PCI enrollment. Blue points (Treatment 2: Digital Training + Tablet) and orange points (Treatment 1: Tablet only) indicate the effect sizes. The shapes represent the status of enrollment in PCI: triangle for not being enrolled, and circle for being enrolled. Horizontal lines denote 95% confidence intervals.

Figure C7: Heterogeneity Plot for Short-Term Effects (Dependent or Minor in Care)



Notes: This graph shows how treatment effects vary depending on whether participants have a dependent or minor in care. Blue points represent Treatment 2 (Digital Training + Tablet), while orange points represent Treatment 1 (Tablet only). Shapes indicate the dependent status: triangles for those without a dependent and circles for those with one. Horizontal lines denote 95% confidence intervals.

Figure C8: Heterogeneity Plot for Medium-Term Effects (Dependent or Minor in Care)



Notes: This graph shows how treatment effects vary depending on whether participants have a dependent or minor in care. Blue points represent Treatment 2 (Digital Training + Tablet), while orange points represent Treatment 1 (Tablet only). Shapes indicate the dependent status: triangles for those without a dependent and circles for those with one. Horizontal lines denote 95% confidence intervals.

Table C1: Heterogeneous Effects by Gender (short-term effects)

	Working	Digital Skills	Job Search	Life Satisfaction	E-Gov Use
T1	0.036	0.263***	0.122*	0.097	−0.044
	(0.025)	(0.070)	(0.069)	(0.099)	(0.086)
Female×T1	−0.031	−0.137	0.012	−0.122	0.028
	(0.028)	(0.103)	(0.081)	(0.114)	(0.100)
T2	0.001	0.471***	0.279***	0.211**	0.194**
	(0.019)	(0.107)	(0.065)	(0.099)	(0.085)
Female×T2	−0.011	0.034	−0.011	−0.137	−0.060
	(0.026)	(0.121)	(0.085)	(0.113)	(0.107)
Mean (C)	0.112	0.101	0.040	2.945	0.230
Obs.	2247	2247	2247	2247	2247

Notes: This table reports the intervention effects on five key outcomes, stratified by gender. We extend our preferred specifications from Table A8 (with full controls and baseline outcome values) by including a dummy variable for female participants, and its interaction with the treatment dummies (T1 and T2). "Working" is an indicator for self-reported employment, and "Life Satisfaction" is on a 1–5 scale. "Digital Skills", "Job Search", and "E-Gov Use" are standardized composite indicators (following Anderson 2008), with coefficients interpreted in standard deviations (see Appendix for details). Standard errors (in parentheses) are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table C2: Heterogeneous Effects by Education (short-term effects)

	Working	Digital Skills	Job Search	Life Satisfaction	E-Gov Use
T1	0.005	0.245**	0.079	−0.038	0.070
	(0.032)	(0.095)	(0.084)	(0.173)	(0.082)
Complete Primary×T1	−0.008	−0.054	0.056	0.097	−0.048
	(0.038)	(0.123)	(0.128)	(0.201)	(0.111)
Secondary×T1	0.024	−0.120	0.051	0.053	−0.185
	(0.037)	(0.118)	(0.103)	(0.187)	(0.129)
T2	−0.008	0.550***	0.199*	0.013	0.154
	(0.027)	(0.118)	(0.106)	(0.158)	(0.098)
Complete Primary×T2	0.023	0.020	0.128	0.131	0.039
	(0.035)	(0.153)	(0.146)	(0.193)	(0.126)
Secondary×T2	−0.019	−0.136	0.054	0.098	−0.019
	(0.033)	(0.134)	(0.122)	(0.188)	(0.146)
Mean (C)	0.112	0.101	0.040	2.945	0.230
Obs.	2247	2247	2247	2247	2247

Notes: This table reports the intervention effects on five key outcomes, stratified by education level. We extend our preferred specifications from Table A8 (with full controls and baseline outcome values) by including a categorical education variable, where "incomplete primary" serves as the baseline category, and its interaction with the treatment dummies (T1 and T2). "Working" is an indicator for self-reported employment, and "Life Satisfaction" is on a 1–5 scale. "Digital Skills", "Job Search", and "E-Gov Use" are standardized composite indicators (following Anderson 2008), with coefficients interpreted in standard deviations (see Appendix for details). Standard errors (in parentheses) are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table C3: Heterogeneous Effects by Education (medium-term effects)

	Working	Months Worked	Job Retention	Digital Skills	Job Search	Training	Life Satisfaction	E-Gov Use
T1	−0.046	−0.444	−0.440**	0.177	0.066	−0.006	0.017	0.151
	(0.033)	(0.312)	(0.179)	(0.109)	(0.082)	(0.028)	(0.126)	(0.111)
Complete Primary×T1	0.060	0.549	0.484**	−0.020	0.010	0.032	0.135	−0.162
	(0.041)	(0.369)	(0.223)	(0.134)	(0.113)	(0.040)	(0.160)	(0.129)
Secondary×T1	0.067*	0.749**	0.438**	0.005	0.031	0.026	0.069	−0.229*
	(0.039)	(0.343)	(0.208)	(0.131)	(0.093)	(0.035)	(0.148)	(0.133)
T2	0.007	−0.183	0.270	0.339***	0.148*	−0.042	−0.036	0.219**
	(0.030)	(0.232)	(0.386)	(0.118)	(0.083)	(0.027)	(0.138)	(0.090)
Complete Primary×T2	0.001	0.663**	−0.275	0.003	−0.032	0.036	0.259	−0.012
	(0.036)	(0.315)	(0.398)	(0.150)	(0.115)	(0.038)	(0.180)	(0.100)
Secondary×T2	−0.023	0.111	−0.387	0.100	0.106	0.063	0.160	−0.033
	(0.038)	(0.306)	(0.407)	(0.149)	(0.103)	(0.040)	(0.171)	(0.142)
Mean (C)	0.117	1.317	0.689	0.073	0.129	0.096	2.876	0.237
Obs.	2370	2370	231	2370	2370	2370	2370	2370

Notes: This table reports the intervention effects on five key outcomes, stratified by education level. We extend our preferred specifications from Table A9 (with full controls and baseline outcome values) by including a categorical education variable, where "incomplete primary" serves as the baseline category, and its interaction with the treatment dummies (T1 and T2). "Working" is an indicator for self-reported employment, and "Life Satisfaction" is on a 1–5 scale. "Digital Skills", "Job Search", and "E-Gov Use" are standardized composite indicators (following Anderson 2008), with coefficients interpreted in standard deviations (see Appendix for details). "Job Retention" is defined as keeping a job in the last six months, since the first endline survey. "Months Worked" is the number of months an individual worked in the past year. Standard errors (in parentheses) are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table C4: Heterogenous Effects by Digital Skills (short-term effects)

	Working	Digital Skills	Job Search	Life Satis-faction	E-Gov Use
T1	0.011	0.353***	0.226***	0.032	0.056
	(0.026)	(0.065)	(0.086)	(0.137)	(0.063)
Digital Skills (Q2)×T1	−0.015	−0.160	−0.123	−0.060	−0.069
	(0.038)	(0.114)	(0.116)	(0.160)	(0.119)
Digital Skills (Q3)×T1	0.001	−0.209	−0.061	0.115	0.097
	(0.036)	(0.127)	(0.128)	(0.204)	(0.122)
Digital Skills (Q4)×T1	0.032	−0.306**	−0.163	−0.050	−0.257**
	(0.045)	(0.133)	(0.131)	(0.154)	(0.130)
T2	−0.005	0.491***	0.249***	0.257*	0.218***
	(0.022)	(0.085)	(0.083)	(0.152)	(0.067)
Digital Skills (Q2)×T2	0.009	0.074	−0.095	−0.342*	−0.073
	(0.036)	(0.153)	(0.116)	(0.192)	(0.110)
Digital Skills (Q3)×T2	0.032	0.142	0.198	−0.020	0.088
	(0.040)	(0.157)	(0.136)	(0.191)	(0.131)
Digital Skills (Q4)×T2	−0.056	−0.227	−0.023	−0.143	−0.217
	(0.036)	(0.152)	(0.128)	(0.180)	(0.138)
Mean (C)	0.112	0.101	0.040	2.945	0.230
Obs.	2247	2247	2247	2247	2247

Notes: This table reports the intervention effects on five key outcomes, stratified by the level of digital skills at baseline. We extend our preferred specifications from Table A8 (with full controls and baseline outcome values) by including a categorical variable for quartiles of digital skills at baseline, where the first quartile serves as the default category, and its interaction with the treatment dummies (T1 and T2). "Working" is an indicator for self-reported employment, and "Life Satisfaction" is on a 1–5 scale. "Digital Skills", "Job Search", and "E-Gov Use" are standardized composite indicators (following Anderson 2008), with coefficients interpreted in standard deviations (see Appendix for details). Standard errors (in parentheses) are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table C5: Heterogeneous effects by Digital Skills (medium-term effects)

	Working	Months Worked	Job Retention	Digital Skills	Job Search	Training	Life Satisfaction	E-Gov Use
T1	0.006	0.068	−0.119	0.254***	0.169*	−0.020	0.144	0.074
	(0.025)	(0.210)	(0.184)	(0.082)	(0.087)	(0.029)	(0.097)	(0.073)
Digital Skills (Q2)×T1	0.022	0.210	0.333	−0.049	−0.040	0.080*	0.141	−0.105
	(0.039)	(0.332)	(0.236)	(0.113)	(0.108)	(0.043)	(0.148)	(0.118)
Digital Skills (Q3)×T1	−0.023	−0.044	0.277	−0.198*	−0.093	0.002	0.013	−0.143
	(0.050)	(0.351)	(0.250)	(0.108)	(0.124)	(0.045)	(0.146)	(0.137)
Digital Skills (Q4)×T1	−0.009	0.079	−0.042	−0.048	−0.145	0.067	−0.305**	−0.068
	(0.042)	(0.338)	(0.198)	(0.131)	(0.119)	(0.045)	(0.143)	(0.141)
T2	−0.007	0.052	−0.328	0.350***	0.142	−0.026	0.100	0.174**
	(0.025)	(0.182)	(0.302)	(0.090)	(0.087)	(0.024)	(0.125)	(0.085)
Digital Skills (Q2)×T2	0.045	0.307	0.351	0.082	0.120	0.060	0.135	−0.045
	(0.037)	(0.283)	(0.352)	(0.131)	(0.124)	(0.039)	(0.186)	(0.120)
Digital Skills (Q3)×T2	−0.029	−0.081	0.183	0.021	−0.016	−0.029	0.126	0.003
	(0.043)	(0.349)	(0.376)	(0.112)	(0.124)	(0.046)	(0.163)	(0.144)
Digital Skills (Q4)×T2	0.000	0.020	0.467	0.074	0.039	0.070*	−0.040	0.161
	(0.036)	(0.306)	(0.306)	(0.146)	(0.123)	(0.043)	(0.163)	(0.144)
Mean (C)	0.117	1.317	0.689	0.073	0.129	0.096	2.876	0.237
Obs.	2370	2370	231	2370	2370	2370	2370	2370

Notes: This table reports the intervention effects on eight key outcomes, stratified by the level of digital skills at baseline. We extend our preferred specifications from Table A9 (with full controls and baseline outcome values) by including a categorical variable for quartiles of digital skills at baseline, where the first quartile serves as the default category, and its interaction with the treatment dummies (T1 and T2). "Working" is an indicator for self-reported employment, and "Life Satisfaction" is on a 1–5 scale. "Digital Skills", "Job Search", and "E-Gov Use" are standardized composite indicators (following Anderson 2008), with coefficients interpreted in standard deviations (see Appendix for details). "Job Retention" is defined as keeping a job in the last six months, since the first endline survey. "Months Worked" is the number of months an individual worked in the past year. Standard errors (in parentheses) are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table C6: Heterogeneous Effects by PCI enrollment (short-term effects)

	Working	Digital Skills	Job Search	Life Satisfaction	E-Gov Use
T1	0.006	0.173***	0.156***	0.049	−0.036
	(0.023)	(0.057)	(0.048)	(0.074)	(0.063)
PCI×T1	0.028	0.025	−0.066	−0.091	0.057
	(0.034)	(0.103)	(0.084)	(0.116)	(0.097)
T2	−0.002	0.512***	0.259***	0.084	0.204***
	(0.017)	(0.080)	(0.048)	(0.075)	(0.069)
PCI×T2	−0.014	0.001	0.066	0.105	−0.134
	(0.030)	(0.116)	(0.103)	(0.127)	(0.111)
Mean (C)	0.112	0.101	0.040	2.945	0.230
Obs.	2247	2247	2247	2247	2247

Notes: This table reports the intervention effects on five key outcomes, stratified by PCI receipt. We extend our preferred specifications from Table A8 (with full controls and baseline outcome values) by including a dummy variable for being enroled in PCI, and its interaction with the treatment dummies (T1 and T2). "Working" is an indicator for self-reported employment, and "Life Satisfaction" is on a 1–5 scale. "Digital Skills", "Job Search", and "E-Gov Use" are standardized composite indicators (following Anderson 2008), with coefficients interpreted in standard deviations (see Appendix for details). Standard errors (in parentheses) are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.

Table C7: Heterogeneous Effects by PCI enrollment (medium-term effects)

	Working	Months Worked	Job Retention	Digital Skills	Job Search	Training	Life Satisfaction	E-Gov Use
T1	0.006	0.097	0.086	0.192***	0.112**	0.012	0.105	−0.004
	(0.020)	(0.181)	(0.084)	(0.053)	(0.050)	(0.017)	(0.070)	(0.057)
PCI×T1	0.008	0.027	−0.359**	−0.036	−0.076	0.024	−0.015	−0.042
	(0.030)	(0.256)	(0.144)	(0.086)	(0.082)	(0.035)	(0.123)	(0.113)
T2	0.009	0.259**	0.090	0.393***	0.185***	0.005	0.105	0.227***
	(0.019)	(0.128)	(0.082)	(0.063)	(0.051)	(0.017)	(0.077)	(0.062)
PCI×T2	−0.028	−0.437*	−0.460***	0.023	−0.010	−0.009	0.078	−0.081
	(0.034)	(0.240)	(0.175)	(0.094)	(0.079)	(0.032)	(0.122)	(0.126)
Mean (C)	0.117	1.317	0.689	0.073	0.129	0.096	2.876	0.237
Obs.	2370	2370	231	2370	2370	2370	2370	2370

Notes: This table reports the intervention effects on eight key outcomes, stratified by PCI receipt. We extend our preferred specifications from Table A9 (with full controls and baseline outcome values) by including a dummy variable for being enroled in PCI, and its interaction with the treatment dummies (T1 and T2). "Working" is an indicator for self-reported employment, and "Life Satisfaction" is on a 1–5 scale. "Digital Skills", "Job Search", and "E-Gov Use" are standardized composite indicators (following Anderson 2008), with coefficients interpreted in standard deviations (see Appendix for details). "Job Retention" is defined as keeping a job in the last six months, since the first endline survey. "Months Worked" is the number of months an individual worked in the past year. Standard errors (in parentheses) are clustered at the node level. *: p<0.1, **: p<0.05, ***: p<0.01.