Imperfect Information and the Labor Market: Evidence from Allegheny County*

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Abstract

Abstract goes here

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1 Introduction

Job seekers today have access to an unprecedented amount of online information about opportunities in different occupations, industries, and locations. This information is not always tailored to individuals' personal situations and can be difficult to process, especially for lower-skill searchers and workers with less experience. Several recent studies have tested whether the provision of information about relevant occupations can alleviate search frictions and improve outcomes for workers. While some of these interventions have provided recommendations based on the person's skills and work history, none so far have incorporated individual preferences into the recommendation algorithm.

In this paper, we use a randomized experiment to evaluate the effects of an information intervention on mostly low-income job seekers. We created an online job search tool called *NextUp Jobs* that provides customized information about feasible occupations that are estimated to offer relatively high wages and desirable amenities. The recommendation algorithm first identifies a set of feasible occupations based on local labor demand and the specific user's level of education. The algorithm then ranks each of these occupations by the expected utility from wages (estimated using Current Population Survey data) and from non-wage amenities. We allow preferences for wages and amenities to vary across users based on their inputted ratings of the general importance of four job characteristics: Earning a high wage, being able to work from home, working similar hours each week, and doing no more than moderate physical activity. The resulting page displays a list of 10 to 40 occupations that are predicted to offer the highest levels of expected utility for the job seeker.

We conducted our study in Allegheny County, Pennsylvania in partnership with the Allegheny County Department of Human Services (ACDHS). We recruited a sample of 7,627 individuals in Allegheny County, Pennsylvania and randomly assigned them to receive access to the online platform or not, each with equal probability. Those assigned to the treatment group received a unique link that provided unlimited access to the NextUp Jobs website from any device. The enrollment process included a baseline survey that asked about the participant's employment status, beliefs about the usefulness of job search assistance, and feelings of control over one's life.

We test the effects of the intervention on participants' job search behavior and labor market outcomes using a combination of surveys and administrative data. We collect self-reported employment information from an endline survey administered at 13 weeks after random assignment. Additionally, all treatment group members and a randomly-chosen subset of control group members received short weekly text message surveys asking about their job search activities in the previous week. We have detailed data on the usage of the NextUp Jobs platform, showing how much time each treated participant spent on the site, their inputted preferences, and their clicks on specific occupations. We also link our sample to quarterly unemployment insurance (UI) administrative records to track their employment and earnings outcomes for several quarters after enrollment.

Our results show that...[describe findings]

Our study contributes to the growing literature on personalized digital job search advice. This literature has established that tailored recommendations can influence the breadth and direction of job search, with some evidence of positive effects on employment outcomes. Experiments have tested a range of tools with diverse methods of generating recommended job matches. Several studies provided recommendations based on the job seeker's prior job or their target occupation (Belot, Kircher and Muller, 2019, 2022; Altmann et al., 2023*a*). These recommendations are produced using data on common occupational transitions or the skill distance between occupations.[1] Ben Dhia et al. (2022) evaluate a platform that provides recommendations based on the user's profile, along with general job search advice, planning assistance, and messages of encouragement. Le Barbanchon, Hensvik and Rathelot (2023) create customized lists of job vacancies using a machine learning algorithm based on each user's observed clicks on job ads, such that users who click the same ads receive similar job recommendations. Other platforms have based their recommenda-

[1] Specifically, Belot, Kircher and Muller (2019) and Belot, Kircher and Muller (2022) create lists of alternative occupations that are most related to the job seeker's occupation of interest. The suggested occupations either require similar skills as the person's target occupation or represent frequent employment transitions from the target occupation. The treatment in Altmann et al. (2023*a*) produces recommendations using data on recent labor market transitions from the jobs listed in the user's saved search profile.

tions on labor market demand: Behaghel et al. (2024) guide job seekers towards firm-occupation pairs that are predicted to have greater hiring potential, while Belot et al. (2025) recommend occupations with relatively high ratios of vacancies to job seekers. In perhaps the closest-related study to ours, Baechli, Lalive and Pellizzari (2025) assess each participant's skill profile in a baseline questionnaire and then generate recommendations that are either based on the person's measured skills or on their previous job.

We build upon this literature by directly incorporating the job seeker's preferences into our recommendation algorithm. There are several reasons why factoring in the user's stated preferences could potentially improve automated job search assistance. Job seekers may search more intensively in response to recommendations that align with their personal valuation of various job attributes. Bied et al. (2023) find that online searchers are more likely to apply to recommended jobs when the job aligns more closely with their previous search criteria. They also demonstrate how algorithms that focus only on hiring probabilities can lead job-seekers to search in a direction that reduces their overall expected match utility.[2] At the same time, limiting our recommendations to jobs that are feasibly attainable helps to prevent users from targeting occupations in which they lack relevant experience, as many job-seekers tend to do when they search without assistance (Altmann et al., 2023*b*). Automated tools may therefore lead to better outcomes by recommending occupations that are both feasible *and* attractive for the searcher. Furthermore, the non-pecuniary attributes of jobs are crucial for employee satisfaction (Clark, 2001), but information on these attributes is often difficult to ascertain during the job search. Our intervention makes this information available in a way that minimizes additional cognitive burden on the job seeker, by displaying simple icons in the list of recommended occupations to indicate non-wage amenities.

Beyond the inclusion of preferences, our study extends the literature on digital job search assistance in several other ways. Whereas prior experiments took place in Western Europe, ours takes place in the United States. Unemployed American workers are less likely than their Euro-

[2]This insight relates to a broad body of research showing that ignoring heterogeneity in workers' preferences can lead to frictions and welfare losses in domains such as flexible work scheduling (Mas and Pallais, 2017; He, Neumark and Weng, 2021), job placement intermediation services (Feld, Nagy and Osman, 2022; Banerjee and Chiplunkar, 2024), and employer mandates (Kolstad and Kowalski, 2016).

pean counterparts to receive UI benefits and tend to receive a lower percentage of their previous income through UI (OECD, 2025). European countries such as France and Denmark also operate government-sponsored job boards to assist workers with re-employment, while U.S. job search resources tend to be more fragmented and privatized. These contextual differences raise the possibility that online job search tools may produce different effects in the U.S. than in Europe. Additionally, our sample size of 7,627 participants provides the statistical power to detect treatment effects on administrative employment outcomes that are well within the range of estimates from similar experiments.

Finally, our sample does not consist solely of registered unemployed workers, unlike the samples in nearly all recent studies of online job recommendations. Indeed, 63% of our sample reported being employed at the time they joined the study and only 6% of the non-employed participants received UI benefits in the quarter before they joined. Our sample also contains many people with low earnings capacity; 48% of participants have annual baseline earnings below the poverty line for a single individual ($15,060 in 2024). Our results thus cover a wider range of individuals than in prior work, including on-the-job searchers and highly disadvantaged workers.

2 The NextUp Jobs platform

The NextUp Jobs website was developed by the authors in partnership with ACDHS. The website provides users with customized information about occupations that are likely to be feasible and attractive to them.

Users begin by entering their age, level of education, current or prior occupation (selected from the O*NET occupation database), and zip code. They also rank the importance of the following job characteristics on a five-point Likert scale of "not very important", "not important", "neutral", "important", or "very important":

1. Earning a high wage
2. Being able to work from home
3. Working similar hours each week

4. No more than moderate physical activity

The main page of the site provides a tiled list of 10 to 40 occupations that are predicted to offer the highest levels of expected utility. This list contains the occupation title, a brief description of the occupation, the expected hourly wage, and a description of the occupation's predicted job growth (Appendix Figure D1). Users can click on an occupation to see more information, including the most common tasks that are done on the job and the 25th and 75th percentiles of the predicted wage distribution for the individual user in that occupation. The detail page also indicates when an occupation offers work-from-home opportunities or employer-sponsored health insurance, but it omits this information if the occupation does not offer these specific amenities (Appendix Figure D2).[3] The site also provides a link to occupation-specific job postings on Indeed that are within a 25-mile radius of the user's zip code.

As an information intervention, the NextUp Job site is designed to make users aware of a broader set of occupations than they might otherwise consider. The list of occupations, alongside information about expected wages, characteristics, and real-time job openings for each occupation, is intended to help people learn about new occupations that are good matches for them. The tool does not require that individuals know which occupations to search for, unlike most other online job aggregator websites.

2.1 Methods for generating recommended occupations

Labor economists have long recognized that job seekers care about both wages and non-wage job amenities. We therefore identify attractive occupations for NextUp Jobs users in two steps. First, using information about educational requirements, managerial responsibilities, and transitions across occupations, we identify a set of jobs likely to be feasible for each individual based on their education and current occupation (if they are currently employed) or previous occupation

[3] We classify projected occupation job growth into three categories using the 2020-2030 projections for Pennsylvania from the Pennsylvania Department of Labor and Industry, which closely follows the methodology of the Bureau of Labor Statistics. We divide occupations based on whether projected employment is in the top quintile ("Fast job growth"), the middle three quintiles ("Moderate job growth"), or the lowest quintile ("Slow job growth").

(if they are not employed). Second, we rank the resulting feasible occupations by expected utility. The result is a customized ranking of occupations that reflects both individual-specific wage estimates and individual-specific preferences.

We do not use age, gender, race, or other sensitive demographics to identify attractive occupations. Although these demographic variables might be informative about individuals' opportunities and preferences, we believe this potential benefit is outweighed by the risk of reinforcing existing patterns of discrimination in the labor market.

2.1.1 Step 1 - Identifying feasible occupations

We identify feasible occupations using information on incumbent workers' education, training requirements, observed occupation-to-occupation transitions, and local job postings. Specifically, we only consider an occupation to be feasible for the user if all of the following are true: less than 90% of incumbent workers in the occupation have more education than the user, the occupation transition would not require an extreme amount of retraining or a transition from a non-managerial role to a managerial role, there were at least 150 individuals employed in the occupation in the Pittsburgh metropolitan area in 2021, there was at least one job posting on Indeed in Pittsburgh for the occupation in both March and May 2023, and the transition from the user's current/prior occupation to the target occupation is observed at least once in the Current Population Survey (CPS).[4] This procedure strikes a balance between not being overly restrictive and not providing information on occupations in which it would be extremely difficult to find a job.

[4]We use four education categories when limiting occupations based on educational attainment: up to 12th grade but no high school diploma, at least a high school diploma (or equivalent) and no more than one year of college, two to three years of college, and four years of college or more. We measure the distribution of educational attainment in each occupation using the 2004-2022 CPS monthly files (including the COVID-19 pandemic period of February 2020 to June 2021). To limit retraining requirements, we exclude occupations in O*NET Job Zone 5 (extensive preparation needed, such as lawyers or neurologists) from the feasible set for all users. We exclude occupations in O*NET Job Zone 4 (considerable preparation needed, such as database administrators and cost estimators) for individuals with 10 or more years of potential experience. The number of jobs in Allegheny County in 2021 is measured using data from the Pennsylvania Department of Labor and Industry (https://www.pa.gov/agencies/dli/resources/statistic-materials/dashboards/pa-monthly-workstats.html).

2.1.2 Step 2 - Estimating expected utility

We estimate the expected utility of each occupation for a given NextUp Jobs user by combining estimates of wage and non-wage characteristics with the user's inputted preferences. Specifically, for person i with current/prior occupation o', covariates x_i, preferences over wages ϕ_i, and preferences over amenities ψ_i, their expected utility in target occupation o with vector of amenities z_o is:

$$E[u_{i,o}|x_i, \phi_i, z_o, \psi_i] = \underbrace{E[\ln(w_{i,o}|x_i)]\phi_i}_{\text{wages}} + \underbrace{z_o\psi_i}_{\text{amenities}} \tag{1}$$

Utility from wages. We non-parametrically estimate log wages using generalized random forests (Athey, Tibshirani and Wager, 2019). We specify a separate random forest for each potential target occupation o, which yields potential outcomes as a function of covariates x_i:

$$E[ln(w_{i,o})|x_i] = f_o(x_i)$$

The outputs of the random forest model are the conditional mean and conditional quantiles of the predicted hourly wage for each NextUp Jobs site user (as defined by their inputted characteristics) in each occupation.

We estimate this model using workers observed in the 2002-2019 and 2021-2022 CPS who make occupational transitions during the eight CPS survey months (covering 16 calendar months). We exclude the period of February 2020 to June 2021 to ensure that the results are not driven by the unusual labor market conditions that occurred during the COVID-19 pandemic. The dependent variable of the generalized random forest model is the log hourly wage. The potential explanatory variables are years of education; years of potential work experience (equal to age minus years of schooling minus six, constrained to be non-negative); mean log wages in each state-year; three lagged annual employment changes in the user's state of residence (i.e. Pennsylvania); three lagged annual employment changes in the target occupation (nationwide); three lagged annual predicted employment changes in the state-occupation; three-month lagged averages of the overall nationwide unemployment rate; the nationwide unemployment rate, Pennsylvania unemployment rate, and overall nationwide job vacancy rate (all seasonally adjusted) among people with the user's level of education; the skill distance between the user's current/prior occupation and the target occupation[5]; plus indicators for the current calendar year and month (to capture seasonal patterns) and whether the user is not employed between employment spells.[6]

We estimate the user's preference for wages using their inputted response to the question about the importance of earning a high wage, as described above. The Likert response $R_{i,wage}$ takes values between 1 and 5, with 5 being "very important", and we normalize by the midpoint: $\phi_i = R_{i,wage}/3$.

Combining these elements yields our estimate of expected utility from wages:

$$E[\ln\widehat{(w_{i,o})}|x_i]\phi_i = \underbrace{\hat{f}_0(x_i)}_{\substack{\text{predicted}\\\text{log wage}}} \times \underbrace{\frac{R_{i,\text{wage}}}{3}}_{\substack{\text{stated}\\\text{preference}\\\text{intensity}}} \tag{2}$$

We estimate the generalized random forest using nationwide data. When displaying wages to site users, we adjust wages to account for differences in the occupational wage level in Allegheny County relative to the rest of the country.

Utility from amenities. We also construct expected utility from non-wage amenities in a job. We focus on two amenities: being able to work from home and having a regular schedule. We use data from the CPS and American Time Use Survey on the extent to which people worked from home in 2021 and 2022. We follow Mas and Pallais (2017) in identifying the regular-schedule amenity using the 2001 and 2004 May CPS Work Schedules Supplement. We code an occupation as having an amenity if at least 50 percent of workers in that occupation report having that amenity.

[5]We construct skill distance using 35 different measures of skills from O*NET, such as the level of reading comprehension, mathematics, or equipment maintenance used on the job.

[6]We use the CPS from 2004 onward because we measure the three lagged annual employment changes in the American Community Survey, which begins in 2001. The Bureau of Labor Statistics produces monthly unemployment rates for individuals with less than a high school diploma, a high school diploma but no college, some college or an Associate degree, and a Bachelor's degree or higher.

To ensure comparability with the estimates in equation 3, we translate amenity measures into log dollars using the average willingness to pay estimate as a share of mean wages from Aksoy et al. (2022) and Mas and Pallais (2017).[7] We allow preferences for amenities to vary across job seekers based on the user's inputted five-point Likert responses to the importance of each job characteristic, as mentioned above. We normalize the Likert responses by three, as with wages, so that a person with preferences at the midpoint has the average willingness to pay.

These steps yield our estimate of expected utility from amenities:

$$\widehat{z_o\psi_i} = \sum_k \underbrace{z_{o,k}}_{\substack{\text{indicator}\\\text{for}\\\text{amenity k}}} \underbrace{WTP_k}_{\substack{\text{normalized}\\\text{mean}\\\text{WTP}}} \underbrace{\frac{R_{i,k}}{3}}_{\substack{\text{stated}\\\text{preference}\\\text{intensity}}} \tag{3}$$

3 Study design

We implemented our experiment in partnership with ACDHS. Allegheny County contains the city of Pittsburgh and was the 38th most populous county in the United States in 2024, with a population of 1.2 million people. ACDHS administers a variety of social services including homeless shelters, child protective services, and support for economically vulnerable families with young children.

Labor market conditions in Allegheny County were similar to the national average during our study period. The county unemployment rate was 3.3% at the beginning of the study in October 2023 and 4.1% in January 2025, compared with nationwide rates of 3.6% and 4.4% in these months (U.S. Bureau of Labor Statistics Local Area Unemployment Statistics). Allegheny County's labor force participation rate was 65.1% among residents 16 years and over in 2023, compared with 63.8% for the U.S. as a whole (American Community Survey 2023 1-year estimates Table DP03).

[7] These log dollar values are 1.08 for being able to work from home and 1.74 for having a regular schedule. However, these values were erroneously hard-coded as 2 and 3, respectively, in the version of the recommendation algorithm that was implemented in our study.

3.1 Recruitment

We recruited our sample on a rolling basis through a combination of direct targeted outreach and public advertisements. In October 2023, ACDHS began sending out waves of text messages to people in its administrative records who were 18 to 44 years old and had UI earnings between $0 and $25,000 in the most recent available calendar quarter of data. The text messages encouraged people to sign up for the study and provided a link to the baseline survey. Those who had not yet completed the survey received follow-up texts two days and four days after the initial text.

In November 2023, ACDHS staff began calling subsets of the individuals who received text messages and still had not completed the baseline survey. The phone calls took place after the person had received their second follow-up text. If the person did not answer the call, the caller left a voicemail describing the NextUp Jobs study and encouraging the person to sign up. ACDHS then sent a fourth and final text message, followed by a second phone call. The second call did not leave a voicemail. The text message campaign ended on January 22, 2025 and the phone outreach ended on February 9, 2025. In total, ACDHS texted 221,070 people and called 32,033 people on our behalf.

In addition to the targeted outreach, ACDHS advertised the study to the general public through community outlets. These efforts included a social media ad campaign, a link on the employment services page of the ACDHS website, a blurb in the American Job Center email newsletter for Allegheny County, messages on digital billboards on the campus of the local community college, and fliers posted on bulletin boards in local shops and public buildings. ACDHS staff also promoted the study by handing out fliers at various resource fairs and community events.

A total of 7,645 individuals enrolled in the study: 7,226 from the targeted version of the baseline survey and 419 from the publicly-available version. Thirteen of these individuals are duplicates and are excluded from the study sample. Another five people are excluded because they were under age 18 when they enrolled. The resulting sample contains 7,627 individuals.

3.2 Baseline survey

All enrollees entered the study by completing a baseline survey. The individuals who received targeted recruitment messages were given a personalized link to a version of the baseline survey that paid a $10 digital gift card upon completion. The non-targeted materials that advertised the study to the general public led to a separate unincentivized version of the baseline survey that was otherwise identical to the targeted version.

The baseline survey began by describing the NextUp Jobs study and explaining that access to the job search tool was allocated randomly. The survey then screened the person's study eligibility. Prior to November 6, 2024, respondents were screened out as ineligible if they said they did not live in Allegheny County. We changed this criterion on November 6, 2024 such that respondents were only screened out if they reported living outside Pennsylvania.[8] For the targeted version of the baseline, respondents were allowed to participate even if their self-reported name and date of birth did not match the identity of the person who received the targeted outreach.

After this initial screen, the survey asked questions related to employment and beliefs about the usefulness of job search assistance, as well as financial stability, mental health, feelings of control over one's life, and subjective well-being.[9] The survey ended by telling respondents that they would hear back within one week if they were selected to receive access to the job search tool.

3.3 Random assignment and onboarding

New study enrollees were processed on a weekly basis. Enrollees were assigned to the treatment or control group using simple individual-level random assignment with a 50% probability for each group. The treatment group was offered open-ended access to the job search tool, while the control

[8]We altered this screening criterion in an effort to increase the volume of eligible participants by expanding eligibility to people who live in Pennsylvania but outside Allegheny County. We maintained the Pennsylvania residency requirement because we only have access to UI administrative records (i.e. can only measure administrative employment outcomes) for study participants who work in Pennsylvania.

[9]The survey used the same four-part locus of control question as the National Longitudinal Survey of Youth 1979, the same life satisfaction question and ability to cover an unexpected expense question as the Federal Reserve Survey of Household Economics and Decision-making, and the two-part depression screener and two-part anxiety screener from Kroenke et al. (2009).

group did not receive access to the tool.

Participants were not directly notified about their random assignment outcome. Control group members received no follow-up communications after random assignment (apart from survey outreach, described below). The treatment group received a text message from ACDHS on the first Wednesday after their random assignment. The text contained a personalized link to the job search tool.[10] This text was sent once a week on Wednesdays at 10 am for up to four weeks, or until the participant visited their unique link to the job search tool for the first time. The treatment group also received emails with the same information as in the texts. The emails were sent on Monday and Friday at 10 am for up to 4 weeks, starting on the first Monday or Friday after the person's random assignment. The emails stopped once the person visited their unique link to the tool. Additionally, treatment group members received one letter and one phone call from ACDHS if they had not visited the website within roughly two weeks after random assignment.

3.4 Incentives to use the website

To incentivize use of NextUp Jobs, we offered treatment group participants a $10 digital gift card if they spent at least 10 minutes on the website in the 21 days after they first received their link to the site. We then made this same offer a second time on May 22, 2025 to further increase engagement with the site.

We also invited randomly-selected subsets of treatment group members to attend workshops held in person at the ACDHS office in downtown Pittsburgh. During these one-hour workshops, an ACDHS staff member gave a brief presentation on how to use the NextUp Jobs tool. Workshop attendees then spent the rest of the hour searching for jobs using the NextUp Jobs tool and other online resources. Each attendee received a prepaid Visa debit card at the end of the workshop. The amount of the incentive varied across workshop sessions and was either $50, $100, or $200 per session. Study participants were only allowed to attend one workshop. We held 39 workshop

[10]The personalized URL was "https://nextupjobs.alleghenycounty.us/Dashboard/X", where X is a 9-character alphanumeric string that is randomly assigned to each person. This random string in the URL was intended to make it more difficult for individuals in the treatment group to share the link with other people. It also allowed us to track each participant's activity on the site without requiring them to log in with a username and password.

sessions with 158 total participants. The average attendee's workshop took place 48 days after random assignment. Some people attended their workshop as soon as one day and as late as 309 days after random assignment.

4 Data and sample

4.1 Administrative data

We link the study participants to Pennsylvania UI records, which exclude jobs such as independent contracting and informal work. The data reports whether an individual had UI-covered employment in each calendar quarter, and how much money the person earned from each of their respective employers in the quarter. The data also reports the amount of UI benefits that the person received in each quarter, if any. The UI data is matched with the study sample based on Social Security Number. The data is available for at least 95% of participants in each quarter starting with the sixth quarter prior to random assignment and for at least 86% of participants in each quarter going back to 12 quarters prior to random assignment.[11] We use this data to construct an unbalanced panel of employment outcomes for up to 12 quarters prior to and five quarters following an individual's study enrollment date.

Our data-sharing partnership with ACDHS also enables us to observe participants' involvement in a variety of social services, including Medicaid, SNAP, TANF, SSI, Section 8 rental housing subsidies, Head Start, and child care subsidies. All of these records are linked using a common individual-level identifier within the ACDHS database.

4.2 Follow-up surveys

Endline survey. We administered an endline survey that asked the same questions as in the baseline survey. All study participants received the endline survey on the first Monday that was at least 91 days after their random assignment date. Participants had 30 days to complete the survey.

[11] UI records could not be obtained for certain SSN's in the sample due to restrictions in the data sharing agreement with ACDHS.

Participants received a link to the survey via text message. Those who had not yet completed the survey received reminder texts two days and four days after the initial text. Those who still had not completed the survey after two to three weeks received an email, a letter, and a phone call from ACDHS. Prior to January 18, 2025, participants received a $25 digital gift card for completing the survey. We then lowered the incentive to $10 starting on January 18, 2025 in order to reduce research costs.

Job search surveys. All treatment group members and a subset of control group members received a text message on the first Friday after their random assignment date with an invitation to opt into a stream of short, chatbot-style text message surveys. These surveys were sent out on a weekly basis on Fridays for the first 12 weeks after the person joined the study. Participants were able to opt out of the stream of surveys at any time. The surveys were unincentivized. Each survey asked the same set of questions. The first question asked how many jobs the person applied to in the past seven days. Those who responded with a nonzero value were then asked about the titles of one or two of the jobs to which they applied.

The receipt of weekly job search diaries by itself could potentially affect a person's job search behavior and employment outcomes independently of their access to the NextUp Jobs tool. To explore this possibility, we began excluding a randomly-chosen subset of control group members from the weekly job search diaries starting midway through the study enrollment period. All new enrollees who were assigned to the control group beginning on December 9, 2024 were randomized with equal probability to be invited or not invited to the 12-week stream of diaries. This additional layer of random assignment creates a third experimental arm that we refer to as the "no-diary" control group. We estimate the independent causal effect of the job search diaries by comparing the outcomes of the 3,126 control subjects who were invited to the diaries with the 715 control subjects who were not. All control group members received the endline survey regardless of their eligibility for the job search diaries.

4.3 Sample description

Table 1 presents the baseline characteristics of the 7,627 study participants. The sample is 69% female and 39% Black. The mean sample member was 35 years old upon enrollment. Two-thirds of participants received Medicaid in the year prior to joining the study, while 57% received SNAP benefits. Only 63% of participants reported being currently employed in the baseline survey. This percentage aligns closely with administrative UI records, which show that 65.5% of participants had any paid employment in the calendar quarter prior to their quarter of enrollment. The relatively low socioeconomic status of the sample is not surprising given that the majority of participants came from a social services agency that tends to serve a disadvantaged subset of Allegheny County residents.

Overall, the results in Table 1 show that the randomization yielded treatment and control groups that are well-balanced on focal baseline characteristics.

Table A3 compares the 7,226 targeted recruits who chose to participate in the study with the 213,844 targeted recruits who chose not to participate. Relative to the full group of targeted recruits, the study participants are more likely to be female and Black, and more likely to have received Medicaid and SNAP in the year prior to recruitment. The participants were 5.4 pp more likely than the non-participants to be employed in the quarter before recruitment, yet they also had $726 lower average earnings (including zeroes) than the non-participants in this quarter.

5 Empirical strategy

We estimate the intent-to-treat (ITT) effects of our intervention using linear regressions of the form:

$$Y_i = Z_i^T \gamma_T + X_i' \mu + \eta_i, \tag{4}$$

where Y_i denotes a post-randomization outcome of individual i (e.g., quarterly earnings), Z_i^T is an indicator for individual i being randomly assigned to the treatment group, and X_i is a vector that contains an intercept and baseline covariates to address small baseline imbalances and increase precision. We use centered covariates (i.e. demeaned using the sample-wide mean) that are fully interacted with the treatment indicator in order to improve the asymptotic precision of the treatment effect estimates (Lin, 2013). Standard errors are clustered at the individual level. This regression estimates the effect of being randomly assigned to receive access to the job search tool relative to not receiving access.

We also estimate local average treatment effects (LATE) using the following two-stage least squares regression:

$$Y_i = D_i \tau + X_i' \beta + \epsilon_i \tag{5}$$

$$D_i = Z_i^T \pi + X_i' \theta + \nu_i, \tag{6}$$

where D_i is an indicator for whether individual i has spent a minimal amount of time on the NextUp Jobs website. The random assignment indicator Z_i^T is an instrumental variable for whether individuals take up the offered intervention, D_i.

Our preferred definition of treatment take-up is spending at least 10 total minutes on the website, but we present estimates for alternative take-up thresholds ranging from one minute to 100 minutes spent on the site. Under the assumption that individuals in the control group do not access the website [12], the resulting estimate of τ can be interpreted as the average treatment effect among individuals who spend the designated amount of time on the website (i.e. the average treatment effect among the treated).

We did not specify the exact regression covariates X_i in our pre-analysis plan. Our benchmark specification adjusts for the following self-reported characteristics from the baseline survey: age, Black (y/n), female (y/n), currently employed (y/n), and level of education. We also adjust for the lagged outcome in the pre-randomization period when possible, such as when analyzing UI

[12] It is possible that some control subjects accessed the site using a treatment subject's personalized link. Based on participants' self-reported addresses from the baseline survey, there are no clusters of participants that share the same home address and span the treatment and control groups. It is therefore unlikely that treatment spillovers occurred in the form of household members sharing their site links with each other.

employment outcomes. We test robustness with specifications that do not include any covariates and specifications that use data-driven methods to select covariates from our high-dimensional set of baseline characteristics from administrative data and the baseline survey. In particular, we implement two machine learning estimation methods as robustness checks. First, we select OLS covariates using a post-double LASSO procedure (Belloni, Chernozhukov and Hansen, 2014). Second, we estimate average treatment effects nonparametrically using generalized random forests (Athey, Tibshirani and Wager, 2019).[13]

Many of our focal study outcomes are measured at multiple time points after enrollment, such as quarterly UI earnings or responses to the weekly job search diaries. Our benchmark approach is to treat each time point as a separate cross-sectional dataset. For example, to estimate treatment effects on UI earnings in each quarter after enrollment, we run separate regressions for each quarterly earnings measurement. We also use cross-sectional regressions with outcomes that are pooled over the entire post-enrollment study period and weighted by the total number of possible observations, such as when estimating effects on the number of job applications from the diary surveys. Where appropriate, we test the robustness of the pooled cross-sectional results by using panel data models.

As mentioned in Section 4.2, our study included a second layer of random assignment that excluded some control group members from the 12-week stream of job search diaries. We use the same regressions as above to compare the outcomes of the diary-eligible versus diary-ineligible control group members. This comparison isolates the independent causal effect of receiving job search surveys on a person's outcomes. For these comparisons, we limit the analytic sample to control group members who joined the study on or after December 9, 2024 because this is when

[13]The set of potential controls for the machine learning methods includes: all items from the baseline survey, indicators for the calendar month and year of enrollment, quarterly employment and earnings in the 12 quarters preceding study enrollment, various measures of Medicaid-funded health care utilization in the year before enrollment, criminal justice system involvement in the year before enrollment, and receipt of various social services such as SNAP, TANF, SSI, Medicaid, Section 8, and child care subsidies. We impute missing values of controls using the median value of the variable within each study arm. We also include indicator variables for the missingness of each control, as recommended in Zhao and Ding (2024). For the impacts on Q1 UI earnings, the post-double LASSO procedure typically selects the indicator for being currently employed, the indicator for working in an occupation that pays above-median wages in the CPS data, and pre-treatment UI earnings measures.

the random assignment of diary eligibility began.

5.1 Pre-registered outcomes

Our primary pre-registered outcomes from administrative UI records are:

1. Indicators for whether the participant is employed
2. Indicators for whether the participant has quarterly earnings above a certain threshold
3. The participant's amount of quarterly earnings (with and without adjustments for outliers).

These outcomes are measured in each of the first four complete calendar quarters after the quarter in which the person joined the study. Our primary pre-registered outcomes from the endline survey include:

1. Measures of subjective well-being, financial security, mental health, and whether the participant believes they have a good idea of the types of jobs that are good matches for them
2. Measures of the expected utility from the participant's current or prior self-reported occupation
3. Indicators for whether the participant's current or prior self-reported occupation pays a high wage relative to other occupations. This analysis is based on the 2023 Current Population Survey Merged Outgoing Rotation Group (CPS MORG) data and is conditional on the person's level of education as reported in the baseline survey.

Our secondary pre-registered outcomes come from the weekly job search diaries:

1. Job search intensity, as measured by the mean number of applications the person reported submitting per week across all of their diary responses
2. Direction of job search: a) Did the person apply to jobs that are relatively high-wage? b) Did the person apply to jobs that were recommended to them by the algorithm on the NextUp Jobs website?

6 Results

6.1 Treatment take-up

We begin by examining the first-stage effect on take-up of the job search tool. Among the treatment group, 65.3% of participants visited the NextUp Jobs website at least once (Table 2); 43.0% spent at least 5 total minutes on the site, 35.1% spent at least 10 minutes, and 11.1% spent at least 100 minutes. The median time spent on the site was 12.5 minutes and the mean was 75 minutes (Figure 1). Black participants were 10 pp more likely than White participants to visit the site at least once, and women were 6.2 pp more likely to visit the site than men.

6.2 Job search behavior

The NextUp Jobs platform could influence the intensity and direction of job search by recommending relatively attractive occupations that the user may not otherwise consider. We measure the intensity of participants' job search efforts using the weekly job search diaries. Each diary asked how many jobs the person applied to in the past seven days. If the person reported applying to at least one job, the survey then asked for the title of one or two of the jobs. We translated the self-reported job titles into Census occupation codes using a generative AI tool.[14]

Table 9 presents the results. The control group reported applying to an average of 3.72 jobs per week. Across specifications, we find small and statistically insignificant ITT effects on this outcome. Our benchmark estimate in column 3 rules out increases of more than 16% of the control mean and reductions of more than 8%. Among the participants who reported applying to at least one job, the treatment did not lead them to apply to occupations with higher expected utility. It also did not make participants more likely to apply to occupations that are above the median education-adjusted earnings across all occupations in the 2023 nationwide CPS MORG data.

At the same time, the treatment appears to have modestly increased the likelihood of applying to occupations that the NextUp Jobs algorithm would have recommended to the person based on their personal information and stated job preferences. The ITT effect ranges from 3 to 5 pp across specifications, on a base of 37.1%. The treatment also led participants to apply to occupations with higher-ranked personal utility within the set of occupations that our algorithm would have recommended to them. Our preferred ITT estimate is a 9.9% increase from the control mean.

[14]Appendix Section C.2 explores selection into diary response on observable baseline characteristics. 43.3% of eligible participants completed at least one diary. Control subjects were 3.6 pp more likely than treatment subjects to complete at least one diary.

The tool did not meaningfully affect the intensity of job search. Conditional on applying to a job, however, the tool seems to have modestly altered the direction of search towards occupations that a) would have appeared at all in our algorithm's recommendation set for the given user, and b) are ranked more highly within our algorithm's recommendation set for the user.

6.3 Occupation characteristics

The recommendations from our platform could lead participants to switch to a new occupation. The baseline and endline surveys both asked participants about their current occupation (if they reported being currently employed) and their most recent occupation (if they reported not being employed). Respondents chose from a drop-down list of occupation titles from the O*NET database. These responses enable us to observe occupation switches between the baseline and endline surveys. We examine switches at the 2-digit, 4-digit, and 6-digit SOC code level. 36.9% of control group members reported an occupation at endline that had a different 2-digit SOC code than their baseline occupation. This rate was slightly lower for the treatment group, with regression-adjusted impacts ranging from -1.4 to -1.7 pp across specifications. The confidence intervals of these effects include zero, but they generally rule out positive effects larger than 2 pp.

The treatment did not impact the likelihood that endline survey respondents reported working in a relatively high-paying occupation. This outcome is measured by calculating the percentile rank of the person's endline occupation among all occupations in the 2023 nationwide CPS MORG data in terms of education-adjusted median earnings. 32.7% of control subjects reported working in a current occupation at endline that fell above the median earnings across all occupations in the CPS data. The treatment had small positive effects on this likelihood that are not distinguishable from zero (Table 6). The LATE effects are larger but still noisy (Table 7), and the point estimates are relatively stable across thresholds of take-up (Table 8).

The treatment also did not yield detectable impacts on the expected utility of the occupations in which endline survey respondents reported working. We estimate the expected money-metric utility of the person's occupation using an approach similar to the calculation described in Section

2.1.2, with two changes. First, we measure preferences for wages and non-wage amenities from the person's baseline survey responses instead of from their inputs on the NextUp Jobs website.[15] Second, we include a third non-wage amenity, doing no more than moderate physical activity on the job, which is not used in the website's recommendation algorithm.

6.4 Employment outcomes

The ultimate goal of our online job search assistance tool is to increase workers' earnings. Table 3 presents the ITT impacts on employment and earnings outcomes measured from UI administrative records in the first complete quarter (Q1) after the quarter of random assignment. This outcome data is available for 81% of the study sample at the time of this writing. The following results are therefore subject to change as we acquire data for the rest of the sample. 65.6% of the control group had employment in this quarter. The treatment had a small and statistically insignificant effect on the likelihood of employment.

Despite the negligible full-sample effect on Q1 employment, the treatment may have *reduced* Q1 total earnings by up to $373, or 6% of the control group mean (Table 3). The participants who were below the top quartile of pre-treatment earnings stand out with a negative Q1 earnings impact of $679 (Table 10 panel B), compared with an estimated earnings gain of $1,406 among those with pre-treatment earnings in the top quartile.

The LATE impacts on Q1 employment outcomes exhibit a similar pattern of results as the ITT effects. Among those who spent at least 10 minutes using the website, the treatment had a negative point-estimated effect on Q1 earnings (Table 4). Our preferred specification rules out earnings decreases larger than $975 and gains larger than $381. The LATE impact on employment is negligible, with stable estimates across thresholds of treatment take-up (Table 5).

We complement the UI-based measure of employment with a self-reported measure from the

[15]The baseline survey asked the same four Likert-scale questions as the website: Rank the importance of earning a high wage, working similar hours each week, being able to work from home, and doing no more than moderate physical activity.

endline survey.[16] 65.3% of control group respondents reported being currently employed, which aligns very closely with the 65.6% Q1 employment rate from UI records. Treatment group respondents were 2.1 to 3.3 pp less likely than control respondents to report being employed, with some of the negative impacts reaching thresholds of statistical significance (Table 6). Among endline respondents who spent 10 or more minutes using the tool, we estimate a statistically significant negative effect of 5.5 to 6.3 pp on the likelihood of being currently employed (Table 7). The negative effect grows monotonically in size as the take-up threshold increases, with a negative effect as large as 17.5 pp (26.8%) among those who spent at least 100 minutes on the site (Table 8).

When looking across sample subgroups, there is some evidence that the negative effect on self-reported employment was more pronounced among participants who were not employed at baseline (Table 10 panel C).

6.5 Financial stability and well-being

The endline survey collected data on several downstream outcomes related to financial stability, self-efficacy, and mental health. We observe no detectable ITT impacts on respondents' level of life satisfaction as rated on a 0 to 10 scale (Table 6). Nor do we detect impacts on the strength of a person's internal locus of control or their rates of experiencing mental health challenges during the past two weeks. Treated subjects were not significantly more likely to report being able to pay all of their bills in full this month or being able to pay a $400 emergency expense. We do observe a robust and statistically significant positive impact on the likelihood of agreeing with the statement "My local government tries to improve opportunities for people like me"; the LATE impact on this outcome is as large as 10.3 pp, or 41% of the control mean (Table 7).

[16] The overall endline survey response rate was 53.4%, with an 8 pp higher response rate among the control group than the treatment group (Appendix Table C1). Appendix Section C explores selection into survey response on observable baseline characteristics. We adjust for survey attrition by constructing inverse propensity score weights.

7 Discussion and next steps

These preliminary results provide mixed evidence on the effectiveness of our job recommendation algorithm at improving users' outcomes. While the tool appears to have encouraged users to apply to more jobs, this positive impact does not seem to have led to subsequent gains in employment and earnings. There is some evidence that the intervention *decreased* earnings for the average participant. This draft will be updated to incorporate UI data for the rest of the sample.

Future versions of this paper will include several additional analyses. First, we are working to gather and clean the user activity data from the NextUp Jobs website. This data contains the job preferences and background information that each user inputted into the recommendation algorithm, thus allowing us to see the occupations that the tool recommended to them. We will use this information to construct measures of the expected utility from the participant's current or prior occupation as reported in the endline survey, and then estimate treatment effects on this outcome.

Second, our job search diaries asked respondents to state the title of one or two of the jobs they applied to in the past week, if any. We will categorize these job titles into SOC codes using a generative AI tool that has been trained on this specific task. We will then construct measures of how closely a participant's job applications align with the occupations that the algorithm recommended to them. The treatment effects on this outcome will shed further light on whether the algorithm influenced the direction of the user's job search.

Third, we will continue to refine our treatment effect-estimating models and our approach to correcting for nonresponse bias in the endline survey and job search diaries.

References

Aksoy, Cevat Giray, Jose Maria Barrero, Nicholas Bloom, Steven J. Davis, Mathias Dolls, and Pablo Zarate. 2022. "Working from Home Around the World." NBER working paper no. 30446.

Altmann, Steffen, Anita Glenny, Robert Mahlstedt, and Alexander Sebald. 2023*a*. "The Direct and Indirect Effects of Online Job Search Advice."

Altmann, Steffen, Robert Mahlstedt, Malte Rattenborg, and Alexander Sebald. 2023*b*. "Which Occupations Do Unemployed Workers Target? Insights from Online Job Search Profiles." IZA Discussion Paper 16696.

Athey, Susan, Julie Tibshirani, and Stefan Wager. 2019. "Generalized Random Forests." *The Annals of Statistics*, 47(2): 1148–1178.

Baechli, Mirjam, Rafael Lalive, and Michele Pellizzari. 2025. "Helping Jobseekers with Recommendations Based on Skill Profiles or Past Experience: Evidence from a Randomized Intervention." CESifo working paper 11702.

Banerjee, Abhijit V, and Gaurav Chiplunkar. 2024. "How important are matching frictions in the labor market? Experimental & non-experimental evidence from a large Indian firm." *Journal of Development Economics*, 171: 103330.

Behaghel, Luc, Sofia Dromundo, Marc Gurgand, Yagan Hazard, and Thomas Zuber. 2024. "The potential of recommender systems for directing job search: A large-scale experiment." IZA Discussion Paper 16781.

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen. 2014. "Inference on Treatment Effects after Selection among High-Dimensional Controls." *The Review of Economic Studies*, 81(2 (287)): 608–650.

Belot, Michele, Bart do Koning, Didier Fouarge, Philipp Kircher, Paul Muller, and Sandra Phlippen. 2025. "Advising job seekers in occupations with poor prospects: A field experiment." National Bureau of Economic Research Working Paper 33819.

Belot, Michele, Philipp Kircher, and Paul Muller. 2019. "Providing Advice to Job Seekers at Low Cost: An Experimental Study on Online Advice." *Review of Economic Studies*, 86(4): 1411–1447.

Belot, Michele, Philipp Kircher, and Paul Muller. 2022. "Do the Long-Term Unemployed Benefit from Automated Occupational Advice during Online Job Search?" IZA Discussion Paper 15452.

Ben Dhia, Aïcha, Bruno Crépon, Esther Mbih, Louise Paul-Delvaux, Bertille Picard, and Vincent Pons. 2022. "Can a Website Bring Unemployment Down? Experimental Evidence from France." National Bureau of Economic Research Working Paper 29914.

Bied, Guillaume, Philippe Caillou, Bruno Crepon, Christophe Gaillac, Elia Perennes, and Michele Sebag. 2023. "Designing Labor Market Recommender Systems: How to Improve Human-Based Search."

Clark, Andrew E. 2001. "What really matters in a job? Hedonic measurement using quit data." *Labour Economics*, 8(2): 223–242.

Feld, Brian, AbdelRahman Nagy, and Adam Osman. 2022. "What do jobseekers want? Comparing methods to estimate reservation wages and the value of job attributes." *Journal of Development Economics*, 159: 102978.

He, Haoran, David Neumark, and Qian Weng. 2021. "Do workers value flexible jobs? A field experiment." *Journal of Labor Economics*, 39(3): 709–738.

Kolstad, Jonathan T., and Amanda E. Kowalski. 2016. "Mandate-based health reform and the labor market: Evidence from the Massachusetts reform." *Journal of Health Economics*, 47: 81–106.

Kroenke, Kurt, Robert L. Spitzer, Janet B.W. Williams, and Bernd Löwe. 2009. "An Ultra-Brief Screening Scale for Anxiety and Depression: The PHQ–4." *Psychosomatics*, 50(6): 613–621.

Le Barbanchon, Thomas, Lena Hensvik, and Roland Rathelot. 2023. "How Can AI Improve Search and Matching? Evidence from 59 Million Personalized Job Recommendations."

Lin, Winston. 2013. "Agnostic notes on regression adjustments to experimental data: Reexamining Freedman's critique." *The Annals of Applied Statistics*, 7(1): 295–318.

Mas, Alexandre, and Amanda Pallais. 2017. "Valuing alternative work arrangements." *American Economic Review*, 107(12): 3722–3759.

OECD. 2025. "Benefits in unemployment, share of previous income." Accessed: April 23, 2025.

Zhao, Anqi, and Peng Ding. 2024. "To adjust or not to adjust? estimating the average treatment effect in randomized experiments with missing covariates." *Journal of the American Statistical Association*, 119(545): 450–460.

Tables

Table 1: Baseline sample characteristics

	Treatment	Control	Std. diff.	p-value
Panel A. Demographics				
Age (years)	34.92	34.94	-0.002	0.945
Sex				
Female	0.701	0.682	0.041	0.074
Male	0.284	0.300	-0.034	0.138
Other	0.014	0.018	-0.027	0.231
Race				
Black	0.382	0.390	-0.016	0.490
White	0.588	0.582	0.013	0.568
Other	0.029	0.028	0.008	0.743
Highest education				
Less than high school	0.044	0.034	0.053	0.021
High school	0.348	0.329	0.040	0.083
Some postsecondary schooling	0.329	0.346	-0.037	0.108
Bachelors degree	0.174	0.183	-0.023	0.320
Graduate degree	0.101	0.104	-0.008	0.723
Lives in Allegheny County, PA	0.964	0.965	-0.007	0.763
Panel B. Received public benefits in the 12 months prior to enrollment				
Medicaid	0.676	0.655	0.043	0.060
SNAP	0.577	0.560	0.035	0.136
TANF	0.060	0.051	0.035	0.134
SSI	0.040	0.036	0.017	0.466
Panel C. Employment status and beliefs				
Currently employed	0.634	0.627	0.015	0.511
I would benefit from using a job search tool	0.663	0.674	-0.022	0.328
I know what types of jobs are good matches	0.784	0.801	-0.042	0.067
It would be difficult to find a better job	0.307	0.299	0.018	0.436
Panel D. Employment in the calendar quarter prior to enrollment				
Had any paid employment	0.649	0.657	-0.016	0.488
Total earnings ($; includes zeroes)	5,848	6,146	-0.037	0.113
Received unemployment benefits	0.043	0.043	0.002	0.919
Test for joint orthogonality				
F-stat	1.153			
p-value	0.274			
Total sample size	**3,786**	**3,841**		

Notes: This table shows mean baseline characteristics for the treatment and control groups. The 'std. diff' column reports the standardized mean difference between the two groups. The variables in panels A and C come from the baseline survey. The variables in panel B come from administrative records from the Allegheny County Department of Human Services (ACDHS). The variables in panel D come from Pennsylvania unemployment insurance (UI) records. The omnibus test for joint orthogonality is calculated using randomization inference.

Table 2: NextUp Jobs website usage among treatment group, for full sample and various baseline subgroups

	N	Pct of sample that spent at least X minutes on website					
		> 0 min	≥ 5 min	≥ 10 min	≥ 20 min	≥ 30 min	≥ 100 min
Panel A. By baseline demographics							
Age group							
18 to 24	541	0.617	0.401	0.336	0.246	0.201	0.113
25 to 34	1,408	0.661	0.428	0.344	0.267	0.229	0.116
35 to 44	1,404	0.669	0.450	0.374	0.280	0.231	0.111
45 to 54	257	0.654	0.405	0.315	0.241	0.195	0.089
55 to 64	138	0.601	0.428	0.333	0.254	0.196	0.065
65 and over	38	0.500	0.316	0.263	0.211	0.211	0.158
Sex							
Female	2,655	0.673	0.437	0.356	0.267	0.226	0.116
Male	1,077	0.611	0.411	0.340	0.266	0.216	0.101
Other	54	0.537	0.426	0.315	0.185	0.148	0.037
Race							
Black	1,392	0.714	0.453	0.373	0.289	0.250	0.134
White	2,139	0.614	0.411	0.332	0.248	0.203	0.099
Other	107	0.729	0.477	0.402	0.308	0.243	0.112
Highest education							
Less than high school	167	0.647	0.431	0.365	0.257	0.228	0.132
High school	1,318	0.671	0.430	0.357	0.278	0.233	0.122
Some postsecondary schooling	1,244	0.646	0.440	0.359	0.266	0.219	0.102
Bachelors degree	658	0.647	0.430	0.333	0.260	0.222	0.116
Graduate degree	383	0.642	0.405	0.339	0.243	0.191	0.078
Panel B. By receipt of public benefits in the 12 months prior to enrollment							
Medicaid	2,558	0.671	0.446	0.366	0.280	0.235	0.120
SNAP	2,104	0.678	0.448	0.369	0.285	0.244	0.127
TANF	217	0.733	0.442	0.336	0.272	0.235	0.129
SSI	145	0.690	0.462	0.345	0.262	0.214	0.097
Panel C. By baseline employment status and beliefs							
Currently employed	2,402	0.632	0.406	0.330	0.248	0.203	0.103
I would benefit from using a job search tool	2,506	0.683	0.454	0.372	0.279	0.237	0.121
I know what types of jobs are good matches	2,965	0.654	0.425	0.347	0.260	0.217	0.111
It would be difficult to find a better job	1,160	0.647	0.436	0.352	0.261	0.220	0.108
Panel D. By employment in quarter prior to enrollment							
Had any paid employment	2,380	0.655	0.420	0.344	0.258	0.216	0.112
Above median samplewide earnings	1,829	0.654	0.412	0.334	0.254	0.210	0.113
Received unemployment benefits	159	0.654	0.421	0.365	0.296	0.270	0.132
Full sample	**3,786**	**0.653**	**0.430**	**0.351**	**0.266**	**0.222**	**0.111**

Notes: Table shows the percentage of treatment group members who spent at least a certain amount of time on the NextUp Jobs website, for the full sample and various baseline subgroups. Column 'N' indicates the number of participants in the given subgroup. The subgroups in panels A and C are based on data from the baseline survey. The subgroups in panel B come from administrative records from the Allegheny County Department of Human Services (ACDHS). The variables in panel D come from Pennsylvania unemployment insurance (UI) records.

Table 3: Intent-to-treat effects on employment outcomes in first full quarter after study enrollment

Outcome (N = 6,180)	Control mean	(1)	(2)	(3)	(4)	(5)
Had any paid employment	0.656	-0.009 (0.012)	-0.009 (0.010)	-0.002 (0.008)	-0.002 (0.008)	-0.002 (0.008)
Earnings ($)	6,234	-373.4* (196.4)	-271.9 (166.2)	-147.2 (100.9)	-145.1 (102.1)	-168.9*** (115.9)
Earnings excluding zeroes ($)	9,507	-438.8* (247.0)	-278.0 (211.0)	-158.1 (161.6)	-180.4 (133.6)	-260.1*** (158.7)
Had earnings above $5,000	0.451	-0.025** (0.013)	-0.022** (0.011)	-0.016* (0.009)	-0.014 (0.009)	-0.014 (0.008)
Employer's percentile rank of mean wages in 2023	26.24	-0.373 (0.699)	-0.550 (0.644)	-0.008 (0.511)	-0.500 (0.509)	-0.174 (0.486)
Gained employment since previous quarter	0.053	-0.014*** (0.005)	-0.013** (0.005)	-0.012** (0.005)	-0.015*** (0.005)	-0.014 (0.005)
Lost employment since previous quarter	0.051	-0.001 (0.006)	-0.003 (0.006)	-0.004 (0.006)	<0.001 (0.005)	-0.002 (0.005)
Continued employment since previous quarter	0.603	0.005 (0.012)	0.004 (0.010)	0.008 (0.008)	0.013* (0.008)	0.012 (0.008)
Continued non-employment since previous quarter	0.293	0.011 (0.012)	0.012 (0.010)	0.004 (0.008)	0.003 (0.007)	0.003 (0.007)
New employer(s) since previous quarter	0.218	-0.006 (0.010)	-0.006 (0.010)	-0.004 (0.010)	-0.004 (0.010)	-0.007 (0.010)
New 2-digit NAICS sector(s) since previous quarter	0.175	-0.008 (0.010)	-0.008 (0.009)	-0.008 (0.009)	-0.006 (0.009)	-0.008 (0.009)
New 6-digit NAICS sector(s) since previous quarter	0.199	-0.003 (0.010)	-0.003 (0.010)	-0.002 (0.010)	-0.001 (0.010)	-0.003 (0.010)
Received UI benefits	0.036	0.002 (0.005)	0.001 (0.005)	<0.001 (0.005)	0.002 (0.004)	0.002 (0.005)
Amount of UI benefits received ($)	109.3	-20.49 (15.99)	-21.73 (16.55)	-21.04 (16.38)	-19.09 (15.36)	-17.87*** (15.31)
Adjusts for baseline survey covariates			X	X		
Adjusts for outcome in 4 qtrs before enrollment				X		
Post-double LASSO covariate selection					X	
Causal forest						X

Notes: Table presents estimates of the effect of being assigned to the treatment group on employment outcomes in the first full calendar quarter after the quarter in which the person enrolled in the study. Column (1) regresses the outcome on a treatment indicator with no covariates. Column (2) adjusts for the following self-reported characteristics from the baseline survey: age at enrollment, race, sex, currently employed (y/n), and highest education. Column (3) additionally adjusts for the outcome measured in the four quarters prior to enrollment. Column (4) selects covariates using post-double LASSO. Column (5) estimates the treatment effect nonparametrically using machine learning causal forests. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table 4: Effect of spending at least 10 minutes on NextUp Jobs website on employment outcomes in first full quarter after study enrollment

Outcome (N = 7,627)	Control mean	(1)	(2)	(3)	(4)
Had any paid employment	0.656	-0.027 (0.034)	-0.024 (0.029)	-0.003 (0.023)	0.006 (0.019)
Earnings ($)	6,234	-1,059* (556.7)	-820.9 (508.9)	-296.9 (346.0)	-644.7*** (239.6)
Earnings excluding zeroes ($)	9,507	-1,281* (719.6)	-816.2 (606.3)	-438.0 (433.1)	-1,013*** (325.5)
Had earnings above $5,000	0.451	-0.072** (0.036)	-0.062* (0.032)	-0.051* (0.028)	-0.042 (0.020)
Employer's percentile rank of mean wages in 2023	26.24	-1.06 (1.99)	-1.52 (1.84)	<0.001 (1.49)	0.073 (1.21)
Gained employment since previous quarter	0.053	-0.040*** (0.015)	-0.034** (0.014)	-0.030** (0.014)	-0.008 (0.012)
Lost employment since previous quarter	0.051	-0.004 (0.016)	-0.009 (0.015)	-0.009 (0.016)	-0.008 (0.012)
Continued employment since previous quarter	0.603	0.013 (0.035)	0.010 (0.028)	0.021 (0.023)	0.014 (0.018)
Continued non-employment since previous quarter	0.293	0.031 (0.033)	0.033 (0.028)	0.011 (0.021)	<0.001 (0.018)
New employer(s) since previous quarter	0.218	-0.017 (0.030)	-0.013 (0.029)	-0.007 (0.029)	0.034 (0.023)
New 2-digit NAICS sector(s) since previous quarter	0.175	-0.022 (0.027)	-0.018 (0.027)	-0.020 (0.027)	0.028 (0.022)
New 6-digit NAICS sector(s) since previous quarter	0.199	-0.010 (0.029)	-0.005 (0.028)	-0.002 (0.028)	0.031 (0.023)
Received UI benefits	0.036	0.006 (0.014)	0.005 (0.014)	0.001 (0.013)	0.008 (0.010)
Amount of UI benefits received ($)	109.3	-58.13 (45.42)	-59.14 (45.25)	-60.69 (44.60)	21.96*** (35.03)
Adjusts for baseline survey covariates			X	X	X
Adjusts for outcome in Q-1 through Q-4				X	X
Causal forest					X

Notes: Table presents estimates of the effect of taking up the treatment on employment outcomes in the first full calendar quarter after the quarter in which the person enrolled in the study. Treatment take-up is defined as spending at least 10 minutes on the NextUp Jobs website in total. Columns (1) through (3) use a two-stage least squares regression with the person's assigned treatment status as an instrument for take-up. Column (1) does not include any covariates. Column (2) adjusts for the following self-reported characteristics from the baseline survey: age at enrollment, race, sex, currently employed (y/n), and highest education. Column (3) additionally adjusts for the outcome measured in the four calendar quarters prior to enrollment. Column (4) estimates the LATE nonparametrically using machine learning causal forests. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table 5: Local average treatment effects on employment outcomes in first full quarter after study enrollment, using various thresholds of treatment take-up

		Threshold of treatment take-up					
Outcome (N = 6,180)	Control mean	>0 min	≥ 5 min	≥ 10 min	≥ 20 min	≥ 30 min	≥ 100 min
Earnings ($)							
No covariates	6,234	-572.9*	-870.4*	-1,059*	-1,368*	-1,624*	-3,208*
		(301.2)	(457.5)	(556.7)	(718.6)	(853.6)	(1,691)
Adjusts for baseline survey covariates		-445.2*	-672.8	-820.9	-1,061	-1,302	-2,786
		(270.5)	(416.8)	(508.9)	(673.8)	(835.8)	(1,792)
Additionally adjusts for outcome in Q-1		-225.8	-367.2	-462.6	-663.3	-790.3	-1,524
		(167.0)	(267.6)	(333.2)	(471.6)	(573.1)	(1,178)
Additionally adjusts for outcome in Q-1 through Q-4		-220.9	-354.6	-296.9	-476.8	-494.5	-1,211
		(164.5)	(261.7)	(346.0)	(466.7)	(579.4)	(1,276)
Earnings excluding zeroes ($)							
No covariates	9,507	-674.3*	-1,045*	-1,281*	-1,666*	-1,983*	-3,786*
		(379.1)	(587.3)	(719.6)	(936.0)	(1,115)	(2,136)
Adjusts for baseline survey covariates		-466.1	-678.0	-816.2	-1,115	-1,335	-2,947
		(326.6)	(488.9)	(606.3)	(791.6)	(993.8)	(2,162)
Additionally adjusts for outcome in Q-1		-148.1	-246.2	-344.4	-414.0	-470.8	-503.1
		(276.4)	(383.3)	(461.3)	(613.0)	(733.0)	(1,849)
Additionally adjusts for outcome in Q-1 through Q-4		-226.5	-388.7	-438.0	-615.7	-577.6	-2,010
		(240.8)	(342.9)	(433.1)	(565.6)	(727.0)	(1,732)
Had any paid employment							
No covariates	0.656	-0.014	-0.022	-0.027	-0.035	-0.041	-0.081
		(0.019)	(0.028)	(0.034)	(0.044)	(0.053)	(0.104)
Adjusts for baseline survey covariates		-0.014	-0.018	-0.024	-0.031	-0.037	-0.083
		(0.016)	(0.024)	(0.029)	(0.037)	(0.045)	(0.093)
Additionally adjusts for outcome in Q-1		-0.002	-0.001	-0.002	-0.003	-0.002	-0.006
		(0.013)	(0.019)	(0.024)	(0.030)	(0.036)	(0.075)
Additionally adjusts for outcome in Q-1 through Q-4		-0.003	-0.002	-0.003	-0.003	-0.004	-0.014
		(0.013)	(0.019)	(0.023)	(0.030)	(0.035)	(0.073)

Notes: Table presents estimates of the effect of taking up the treatment on employment outcomes in the first full calendar quarter after the quarter in which the person enrolled in the study. Treatment take-up is defined as spending at least a minimum amount of time on the NextUp Jobs website. We present estimates for different minimum site usage thresholds for robustness. All estimates are from a two-stage least squares regression using the person's assigned treatment status as an instrument for take-up. The regressions that adjust for baseline survey covariates include the following self-reported characteristics from the baseline survey: age at enrollment, race, sex, currently employed (y/n), and highest education. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table 6: Intent-to-treat effects on endline survey outcomes

Outcome	N	Control mean	(1)	(2)	(3)	(4)	(5)
Currently employed	4,170	0.653	-0.033**	-0.030***	-0.021**	-0.021	-0.027**
			(0.015)	(0.011)	(0.011)	(0.011)	(0.012)
Switched occupation since baseline survey (%)							
2-digit SOC code	4,170	0.369	-0.016	-0.017	-0.014	-0.016	-0.016
			(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
4-digit SOC code	4,170	0.464	-0.023	-0.024	-0.022	-0.025	-0.024
			(0.015)	(0.016)	(0.015)	(0.015)	(0.016)
6-digit SOC code	4,170	0.530	-0.005	-0.010	-0.004	-0.007	-0.009
			(0.016)	(0.016)	(0.015)	(0.015)	(0.016)
Occupation is above CPS median earnings (%)							
Current occupation (among those currently employed)	2,531	0.327	<0.001	0.013	0.019	0.014	0.018
			(0.019)	(0.022)	(0.015)	(0.016)	(0.022)
Last occupation (among those not currently employed)	1,434	0.249	-0.020	-0.008	0.009	-0.006	-0.022
			(0.023)	(0.034)	(0.019)	(0.020)	(0.038)
Expected money-metric utility of occupation ($)							
Current occupation (among those currently employed)	1,245	35.11	-0.537	-0.860	-0.175	-0.138	-0.751
			(0.844)	(0.844)	(0.543)	(0.660)	(0.858)
Last occupation (among those not currently employed)	845	30.18	-1.30	-0.550	0.643	-0.843	-1.33
			(0.884)	(1.40)	(0.575)	(0.728)	(1.39)
Agrees with the following statement (%)							
I have a good idea of the types of jobs that are good matches for me	4,115	0.834	0.013	0.016	0.020*	0.017	0.014
			(0.011)	(0.012)	(0.011)	(0.011)	(0.012)
It would be difficult for me to find a better job given my current education and work experience	4,115	0.387	-0.007	-0.014	-0.009	-0.007	-0.014
			(0.015)	(0.015)	(0.014)	(0.015)	(0.016)
My local government tries to improve opportunities for people like me	4,115	0.252	0.050***	0.052***	0.053***	0.051	0.049***
			(0.014)	(0.014)	(0.013)	(0.013)	(0.014)
Agrees with the statement with stronger internal locus of control (%)							
What happens to me is my own doing, OR Sometimes I feel that I don't have enough control over the direction my life is taking	4,095	0.584	0.002	0.007	-0.004	0.001	0.004
			(0.015)	(0.016)	(0.014)	(0.014)	(0.016)
When I make plans, I am almost certain that I can make them work, OR It is not always wise to plan too far ahead because many things turn out to be a matter of good or bad fortune	4,095	0.706	0.002	0.002	0.004	0.004	0.002
			(0.014)	(0.014)	(0.013)	(0.013)	(0.015)
In my case getting what I want has little or nothing to do with luck, OR Many times we might just as well decide what to do by flipping a coin	4,095	0.765	0.005	0.008	-0.001	0.003	0.010
			(0.013)	(0.013)	(0.012)	(0.013)	(0.013)
Many times I feel that I have little influence over the things that happen to me, OR It is impossible for me to believe that chance or luck plays an important role in my life	4,095	0.464	-0.015	-0.018	-0.021	-0.018	-0.014
			(0.016)	(0.016)	(0.015)	(0.015)	(0.016)
Life satisfaction (0-10 scale)	4,084	6.06	0.011	0.033	0.040	0.037	0.024
			(0.074)	(0.076)	(0.064)	(0.066)	(0.077)
Could not pay a $400 emergency expense	4,089	0.405	0.024	0.006	0.009	0.011	0.005
			(0.015)	(0.015)	(0.012)	(0.013)	(0.015)
Able to pay all bills in full this month	4,089	0.470	-0.008	0.003	0.003	0.005	0.005
			(0.016)	(0.015)	(0.012)	(0.013)	(0.015)
Bothered by the following on more than half the days during the past 2 weeks (%)							
Feeling nervous, anxious, or on edge	4,085	0.357	0.011	0.010	0.008	0.005	0.011
			(0.015)	(0.015)	(0.013)	(0.013)	(0.016)
Not able to stop or control worrying	4,085	0.306	0.009	0.005	0.004	0.003	0.005
			(0.015)	(0.015)	(0.012)	(0.013)	(0.015)

Table 6: Intent-to-treat effects on endline survey outcomes *(continued)*

Outcome	N	Control mean	(1)	(2)	(3)	(4)	(5)
Little interest or pleasure in doing things	4,085	0.256	-0.007 (0.014)	-0.012 (0.014)	-0.007 (0.012)	-0.010 (0.012)	-0.011 (0.014)
Feel down, depressed, or hopeless	4,085	0.260	0.013 (0.014)	0.007 (0.014)	0.013 (0.012)	0.010 (0.012)	0.008 (0.014)
Adjusts for baseline survey covariates				X			
Post-double LASSO covariate selection					X		
Causal forest						X	
Includes nonresponse weights							X

Notes: Table presents estimates of the effect of being assigned to the treatment group on self-reported outcomes from the endline survey. The survey took place 13 weeks after random assignment. Column (1) regresses the outcome on a treatment indicator with no covariates. Column (2) adjusts for the following self-reported characteristics from the baseline survey: age at enrollment, race, sex, currently employed (y/n), and highest education. Column (3) selects covariates using post-double LASSO. Column (4) estimates the treatment effect nonparametrically using machine learning causal forests. Column (5) adjusts for the same covariates as in (2) and includes inverse propensity weights for survey nonresponse. Sample sizes differ across survey items because not all respondents answered every question. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table 7: Effect of spending at least 10 minutes on NextUp Jobs website on endline survey outcomes

Outcome	N	Control mean	(1)	(2)	(3)	(4)
Currently employed	4,170	0.653	-0.063**	-0.055**	-0.051***	-0.042
			(0.029)	(0.022)	(0.008)	(0.020)
Switched occupation since baseline survey (%)						
2-digit SOC code	4,170	0.369	-0.030	-0.031	-0.031**	-0.012
			(0.028)	(0.029)	(0.014)	(0.026)
4-digit SOC code	4,170	0.464	-0.044	-0.045	-0.046***	-0.033
			(0.030)	(0.030)	(0.015)	(0.027)
6-digit SOC code	4,170	0.530	-0.009	-0.018	-0.018	-0.017
			(0.030)	(0.031)	(0.015)	(0.027)
Occupation is above CPS median earnings (%)						
Current occupation (among those currently employed)	2,531	0.327	-0.001	0.029	0.036*	-0.005
			(0.037)	(0.044)	(0.019)	(0.027)
Last occupation (among those not currently employed)	1,434	0.249	-0.036	-0.016	-0.042	-0.007
			(0.041)	(0.068)	(0.031)	(0.032)
Expected money-metric utility of occupation ($)						
Current occupation (among those currently employed)	1,245	35.11	-1.01	-1.36	-1.38	-1.00
			(1.59)	(1.53)	(20.01)	(1.03)
Last occupation (among those not currently employed)	845	30.18	-2.31	-0.741	-2.50	-0.448
			(1.57)	(2.85)	(31.62)	(1.20)
Agrees with the following statement (%)						
I have a good idea of the types of jobs that are good matches for me	4,115	0.834	0.025	0.030	0.026***	0.026
			(0.022)	(0.022)	(0.008)	(0.019)
It would be difficult for me to find a better job given my current education and work experience	4,115	0.387	-0.014	-0.025	-0.028*	-0.012
			(0.029)	(0.030)	(0.014)	(0.025)
My local government tries to improve opportunities for people like me	4,115	0.252	0.095***	0.103***	0.094***	0.101
			(0.027)	(0.028)	(0.012)	(0.024)
Agrees with the statement with stronger internal locus of control (%)						
What happens to me is my own doing, OR Sometimes I feel that I don't have enough control over the direction my life is taking	4,095	0.584	0.003	0.014	0.009	-0.036
			(0.029)	(0.030)	(0.015)	(0.024)
When I make plans, I am almost certain that I can make them work, OR It is not always wise to plan too far ahead because many things turn out to be a matter of good or bad fortune	4,095	0.706	0.004	0.002	0.004	-0.005
			(0.027)	(0.028)	(0.013)	(0.023)
In my case getting what I want has little or nothing to do with luck, OR Many times we might just as well decide what to do by flipping a coin	4,095	0.765	0.009	0.015	0.018*	0.031
			(0.025)	(0.026)	(0.011)	(0.022)
Many times I feel that I have little influence over the things that happen to me, OR It is impossible for me to believe that chance or luck plays an important role in my life	4,095	0.464	-0.029	-0.036	-0.026*	-0.010
			(0.030)	(0.031)	(0.015)	(0.027)
Life satisfaction (0-10 scale)	4,084	6.06	0.020	0.026	0.047	0.033
			(0.141)	(0.145)	(0.345)	(0.111)
Could not pay a $400 emergency expense	4,089	0.405	0.046	0.013	0.010	0.045
			(0.029)	(0.028)	(0.013)	(0.022)
Able to pay all bills in full this month	4,089	0.470	-0.016	0.005	0.009	-0.023
			(0.030)	(0.029)	(0.014)	(0.022)
Bothered by the following on more than half the days during the past 2 weeks (%)						
Feeling nervous, anxious, or on edge	4,085	0.357	0.021	0.019	0.020	0.019
			(0.029)	(0.030)	(0.014)	(0.023)

Table 7: Effect of spending at least 10 minutes on NextUp Jobs website on endline survey outcomes *(continued)*

Outcome	N	Control mean	(1)	(2)	(3)	(4)
Not able to stop or control worrying	4,085	0.306	0.017	0.009	0.009	0.017
			(0.028)	(0.028)	(0.013)	(0.022)
Little interest or pleasure in doing things	4,085	0.256	-0.012	-0.024	-0.021*	0.014
			(0.026)	(0.027)	(0.012)	(0.021)
Feel down, depressed, or hopeless	4,085	0.260	0.025	0.015	0.015	0.006
			(0.026)	(0.027)	(0.012)	(0.021)
Adjusts for baseline survey covariates				X	X	
Nonresponse weights					X	
Causal forest						X

Notes: Table presents estimates of the effect of taking up the treatment on self-reported outcomes from the endline survey. The survey took place 13 weeks after random assignment. Treatment take-up is defined as spending at least 10 minutes on the NextUp Jobs website in total. Columns (1) through (3) use a two-stage least squares regression with the person's assigned treatment status as an instrument for take-up. Column (1) does not include any covariates. Column (2) adjusts for the following self-reported characteristics from the baseline survey: age at enrollment, race, sex, currently employed (y/n), and highest education. Column (3) additionally includes inverse propensity weights for survey nonresponse. Column (4) estimates the LATE nonparametrically using machine learning causal forests. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table 8: Local average treatment effects on endline survey outcomes, using various thresholds of treatment take-up

		Threshold of treatment take-up					
Outcome (N = 4,170)	Control mean	$>$ 0 min	$\geq$ 5 min	$\geq$ 10 min	$\geq$ 20 min	$\geq$ 30 min	$\geq$ 100 min
Currently employed	0.653	-0.036***	-0.048***	-0.055**	-0.071**	-0.083**	-0.175**
		(0.014)	(0.018)	(0.022)	(0.028)	(0.033)	(0.068)
Switched occupation since baseline survey (%)							
2-digit SOC code	0.369	-0.020	-0.027	-0.031	-0.039	-0.047	-0.102
		(0.018)	(0.025)	(0.029)	(0.038)	(0.045)	(0.091)
4-digit SOC code	0.464	-0.028	-0.038	-0.045	-0.056	-0.067	-0.138
		(0.019)	(0.026)	(0.030)	(0.040)	(0.047)	(0.095)
6-digit SOC code	0.530	-0.011	-0.015	-0.018	-0.021	-0.025	-0.048
		(0.019)	(0.026)	(0.031)	(0.040)	(0.047)	(0.096)
Occupation is above CPS median earnings (%)							
Current occupation (among those currently employed)	0.327	0.015	0.022	0.029	0.038	0.029	0.055
		(0.027)	(0.037)	(0.044)	(0.055)	(0.068)	(0.132)
Last occupation (among those not currently employed)	0.249	-0.007	-0.014	-0.016	-0.021	-0.026	-0.101
		(0.042)	(0.055)	(0.068)	(0.081)	(0.099)	(0.232)
Agrees with the following statement (%)							
I have a good idea of the types of jobs that are good matches for me	0.834	0.021	0.026	0.030	0.040	0.051	0.120*
		(0.014)	(0.019)	(0.022)	(0.029)	(0.035)	(0.070)
It would be difficult for me to find a better job given my current education and work experience	0.387	-0.019	-0.021	-0.025	-0.035	-0.041	-0.104
		(0.019)	(0.025)	(0.030)	(0.039)	(0.046)	(0.094)
My local government tries to improve opportunities for people like me	0.252	0.063***	0.087***	0.103***	0.134***	0.159***	0.326***
		(0.017)	(0.023)	(0.028)	(0.036)	(0.043)	(0.089)
Agrees with the statement with stronger internal locus of control (%)							
What happens to me is my own doing, OR Sometimes I feel that I don't have enough control over the direction my life is taking	0.584	0.009	0.012	0.014	0.018	0.023	0.053
		(0.019)	(0.025)	(0.030)	(0.039)	(0.047)	(0.094)
When I make plans, I am almost certain that I can make them work, OR It is not always wise to plan too far ahead because many things turn out to be a matter of good or bad fortune	0.706	0.003	0.002	0.002	0.002	0.003	0.019
		(0.017)	(0.023)	(0.028)	(0.036)	(0.043)	(0.086)
In my case getting what I want has little or nothing to do with luck, OR Many times we might just as well decide what to do by flipping a coin	0.765	0.009	0.012	0.015	0.019	0.020	0.038
		(0.016)	(0.022)	(0.026)	(0.033)	(0.040)	(0.081)
Many times I feel that I have little influence over the things that happen to me, OR It is impossible for me to believe that chance or luck plays an important role in my life	0.464	-0.022	-0.029	-0.036	-0.047	-0.057	-0.121
		(0.019)	(0.026)	(0.031)	(0.040)	(0.047)	(0.096)
Life satisfaction (0-10 scale)	6.06	0.039	0.023	0.026	0.032	0.013	0.102
		(0.091)	(0.122)	(0.145)	(0.187)	(0.222)	(0.459)
Could not pay a $400 emergency expense	0.405	0.008	0.011	0.013	0.017	0.024	0.055
		(0.018)	(0.024)	(0.028)	(0.037)	(0.044)	(0.088)
Able to pay all bills in full this month	0.470	0.002	0.003	0.005	0.005	0.002	-0.013
		(0.018)	(0.024)	(0.029)	(0.038)	(0.045)	(0.090)
Bothered by the following on more than half the days during the past 2 weeks (%)							
Feeling nervous, anxious, or on edge	0.357	0.014	0.017	0.019	0.026	0.034	0.090
		(0.019)	(0.025)	(0.030)	(0.039)	(0.046)	(0.093)
Not able to stop or control worrying	0.306	0.007	0.009	0.009	0.013	0.018	0.055
		(0.018)	(0.024)	(0.028)	(0.037)	(0.044)	(0.089)
Little interest or pleasure in doing things	0.256	-0.015	-0.019	-0.024	-0.031	-0.035	-0.053
		(0.017)	(0.022)	(0.027)	(0.035)	(0.041)	(0.085)
Feel down, depressed, or hopeless	0.260	0.009	0.013	0.015	0.020	0.026	0.072
		(0.017)	(0.023)	(0.027)	(0.035)	(0.042)	(0.086)

Notes: Table presents estimates of the effect of being assigned to the treatment group on self-reported outcomes from the endline survey. The survey took place 13 weeks after random assignment. Treatment take-up is defined as spending at least a minimum amount of time on the NextUp Jobs website. We present estimates for different minimum site usage thresholds for robustness. All estimates are from a two-stage least squares regression using the person's assigned treatment status as an instrument for take-up. The regressions adjust for the following self-reported characteristics from the baseline survey: age at enrollment, race, sex, currently employed (y/n), and highest education.. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table 9: Effects on job search behavior

Outcome	N	Control mean	(1)	(2)	(3)	(4)	(5)
Panel A. Intent-to-treat							
Number of jobs applied to in last 7 days	3,280	3.72	0.140 (0.253)	0.092 (0.227)	0.138 (0.226)	0.056 (0.246)	0.356* (0.198)
Mean expected utility of occs applied to	616	30.06	-0.723 (0.880)	-0.471 (1.02)	-0.139 (0.808)	0.192 (0.721)	0.298 (0.766)
Likelihood of applying to an occ that website would have recommended	1,338	0.371	0.051** (0.021)	0.033 (0.022)	0.044** (0.021)	0.041 (0.020)	0.049** (0.021)
Mean percentile utility rank of occs applied to	844	52.62	3.86** (1.72)	6.04*** (1.92)	5.20*** (1.72)	5.28*** (1.67)	6.19*** (1.72)
Likelihood of applying to an occ that is above CPS median earnings	1,247	0.257	0.005 (0.022)	0.037 (0.023)	0.027 (0.020)	0.036 (0.019)	0.032 (0.023)
Panel B. LATE (spent $\geq$ 10 minutes on website)							
Number of jobs applied to in last 7 days	3,280	3.72	0.272 (0.492)	0.063 (0.451)	0.274 (0.732)	-0.997* (0.407)	0.586* (0.327)
Mean expected utility of occs applied to	616	30.06	-1.21 (1.48)	-0.127 (1.29)	-0.238 (2.27)	1.84** (1.17)	0.514 (1.23)
Likelihood of applying to an occ that website would have recommended	1,338	0.371	0.087** (0.035)	0.074** (0.036)	0.076 (0.062)	0.108 (0.034)	0.079** (0.034)
Mean percentile utility rank of occs applied to	844	52.62	6.07** (2.70)	8.24*** (2.69)	8.27** (4.18)	9.80*** (2.55)	9.29*** (2.56)
Likelihood of applying to an occ that is above CPS median earnings	1,247	0.257	0.009 (0.037)	0.055 (0.035)	0.047 (0.059)	0.039 (0.033)	0.052 (0.037)
Pooled data			X	X	X	X	
Panel data							X
Adjusts for benchmark covariates				X	X		X
Includes nonresponse weights					X		
Causal forest						X	

Notes: Table shows treatment effects on self-reported job search behavior as measured from weekly text message job search diary surveys. The LATE estimates use a take-up threshold of spending at least 10 minutes on the website. Columns (1) through (4) use pooled cross-sectional data that averages across each person's diary responses. Column (5) uses panel data with one observation per person per diary response. The benchmark covariate set includes: age at enrollment, race, sex, currently employed (y/n), and highest education. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table 10: Intent-to-treat effects on select outcomes, by baseline subgroups

	Male	Non-male	White	Non-White	Employed	Not employed	Bachelor's or higher	Less than Bachelor's	Above p75 earnings in Q-1	Below p75 earnings in Q-1
Panel A. Had any paid employment in Q1 after enrollment; from UI records										
N	3,084	3,096	3,043	3,057	3,084	3,096	3,084	3,096	3,084	3,096
Control mean	0.660	0.654	0.646	0.670	0.848	0.318	0.725	0.626	0.967	0.545
Treatment effect	-0.004	-0.002	-0.009	-0.004	0.013	-0.014	-0.014	-0.005	0.088	0.002
SE	(0.017)	(0.010)	(0.011)	(0.014)	(0.014)	(0.026)	(0.018)	(0.010)	(0.064)	(0.011)
P-value of diff.	[0.943]		[0.600]		[0.431]		[0.944]		[0.488]	
Panel B. Earnings in Q1 after enrollment ($); from UI records										
N	3,084	3,096	3,043	3,057	3,084	3,096	3,084	3,096	3,084	3,096
Control mean	7,055	5,859	6,704	5,520	8,975	1,412	9,644	4,783	14,830	3,167
Treatment effect	-233.7	-150.0	-110.4	-371.0**	-50.26	-539.4	-378.0	-216.3	1,412	-664.5***
SE	(211.0)	(116.5)	(125.8)	(179.6)	(145.8)	(408.0)	(239.0)	(135.9)	(1,124)	(168.7)
P-value of diff.	[0.867]		[0.397]		[0.523]		[0.662]		[0.020]	
Panel C. Currently employed; from endline survey										
N	1,905	2,265	1,839	2,180	1,905	2,265	1,905	2,265	1,859	2,194
Control mean	0.671	0.646	0.677	0.611	0.885	0.249	0.769	0.604	0.903	0.560
Treatment effect	-0.050**	-0.026	-0.029*	-0.030	-0.006	-0.053**	-0.042	-0.061	-0.041	-0.032**
SE	(0.023)	(0.036)	(0.015)	(0.019)	(0.013)	(0.023)	(0.026)	(0.070)	(0.048)	(0.014)
P-value of diff.	[0.939]		[0.801]		[0.060]		[0.649]		[0.141]	
Panel D. It would be difficult for me to find a better job given my current education and work experience; from endline survey										
N	1,884	2,231	1,818	2,147	1,884	2,231	1,884	2,231	1,838	2,161
Control mean	0.397	0.383	0.426	0.335	0.393	0.376	0.350	0.402	0.398	0.386
Treatment effect	-0.038	-0.032	-0.008	-0.011	-0.027	0.014	0.061	0.020	0.058	-0.020
SE	(0.029)	(0.041)	(0.021)	(0.025)	(0.019)	(0.026)	(0.041)	(0.086)	(0.054)	(0.018)
P-value of diff.	[0.644]		[0.777]		[0.258]		[0.854]		[0.331]	
Panel E. Number of job applications in past 7 days (N); from job search surveys										
N	1,744	1,536	1,688	1,453	1,744	1,536	1,744	1,536	1,701	1,461
Control mean	4.71	3.23	2.92	4.89	2.62	5.57	3.37	3.88	3.00	3.95
Treatment effect	-0.435	0.055	0.264	0.099	0.437*	-0.199	-0.478	-0.226	-1.59*	0.438
SE	(0.511)	(0.987)	(0.282)	(0.389)	(0.248)	(0.571)	(0.958)	(0.779)	(0.933)	(0.276)
P-value of diff.	[0.942]		[0.586]		[0.185]		[0.743]		[0.031]	

Notes: This table reports heterogeneity in intent-to-treat effects on select outcomes across sample subgroups defined by baseline characteristics. The employed/not employed subgroups are defined using data from the baseline survey. The "above p75 earnings in Q-1" subgroup contains participants who had UI earnings above the 75th percentile of the sample in the quarter prior to their study enrollment. The treatment effects in panels C, D, and E adjust for the following self-reported characteristics from the baseline survey: age at enrollment, race, sex, currently employed (y/n), and highest education. The effects in panels A and B additionally adjust for the outcome measured in each of the four complete quarters prior to the person's study enrollment date. The bracketed numbers are the p-values of the differences in treatment effects between the two subgroups on either side of the bracketed number. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

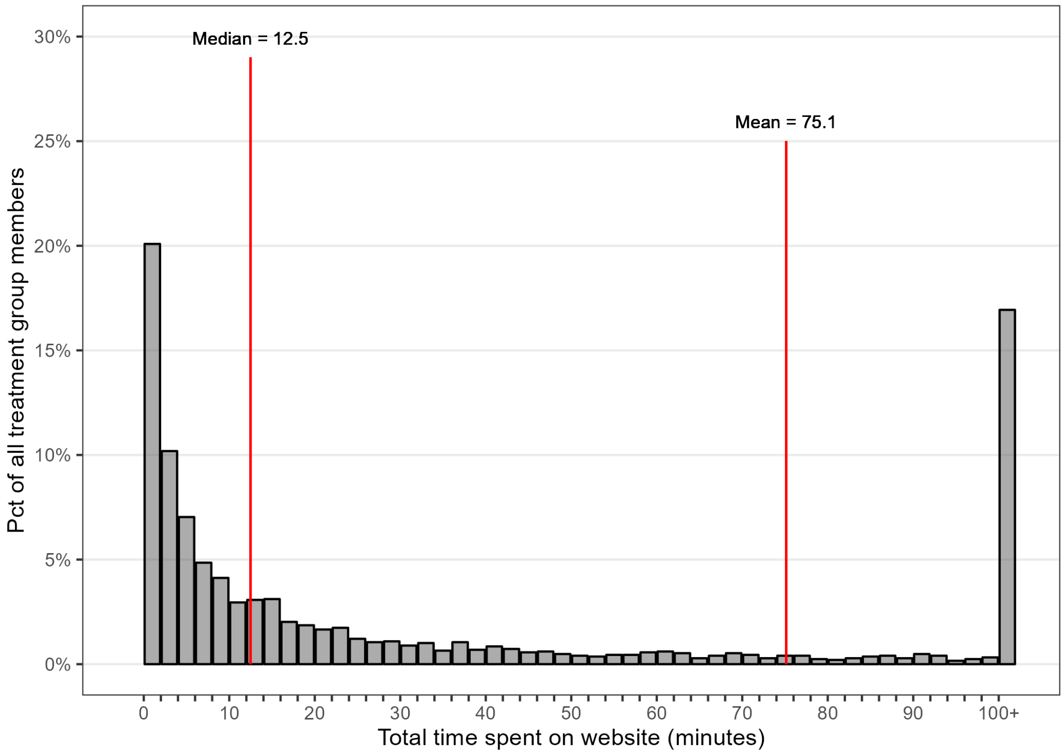
Table 11: Effects of spending at least 10 minutes on the NextUp Jobs website on select outcomes, by baseline subgroups

	Male	Non-male	White	Non-White	Employed	Not employed	Bachelor's or higher	Less than Bachelor's	Above p75 earnings in Q-1	Below p75 earnings in Q-1
Panel A. Had any paid employment in Q1 after enrollment; from UI records										
N	3,084	3,096	3,043	3,057	3,084	3,096	3,084	3,096	3,084	3,096
Control mean	0.660	0.654	0.646	0.670	0.848	0.318	0.725	0.626	0.967	0.545
Treatment effect	-0.009	-0.005	-0.019	0.008	0.019	-0.033	0.008	-0.010	-0.002	-0.006
SE	(0.048)	(0.027)	(0.031)	(0.037)	(0.026)	(0.043)	(0.039)	(0.029)	(0.026)	(0.029)
P-value of diff.	[0.944]		[0.555]		[0.311]		[0.824]		[0.828]	
Panel B. Earnings in Q1 after enrollment $); from UI records										
N	3,084	3,096	3,043	3,057	3,084	3,096	3,084	3,096	3,084	3,096
Control mean	7,055	5,859	6,704	5,520	8,975	1,412	9,644	4,783	14,830	3,167
Treatment effect	-587.6	-415.7	-221.0	-719.0*	-606.3	-292.7	-862.4	-288.2	-29.22	-671.5***
SE	(661.4)	(312.4)	(412.4)	(389.7)	(427.4)	(290.1)	(739.1)	(272.4)	(878.2)	(256.2)
P-value of diff.	[0.873]		[0.453]		[0.332]		[0.394]		[0.320]	
Panel C. Currently employed; from endline survey										
N	1,905	2,265	1,839	2,180	1,905	2,265	1,905	2,265	1,859	2,194
Control mean	0.671	0.646	0.677	0.611	0.885	0.249	0.769	0.604	0.903	0.560
Treatment effect	-0.092**	-0.033	-0.055**	-0.053	-0.020	-0.093**	-0.042	-0.055**	0.032	-0.064**
SE	(0.042)	(0.025)	(0.027)	(0.036)	(0.025)	(0.038)	(0.037)	(0.026)	(0.033)	(0.026)
P-value of diff.	[0.210]		[0.947]		[0.094]		[0.739]		[0.024]	
Panel D. It would be difficult for me to find a better job given my current education and work experience; from endline survey										
N	1,884	2,231	1,818	2,147	1,884	2,231	1,884	2,231	1,838	2,161
Control mean	0.397	0.383	0.426	0.335	0.393	0.376	0.350	0.402	0.398	0.386
Treatment effect	-0.069	<0.001	-0.030	-0.012	-0.042	0.018	0.003	-0.028	0.005	-0.022
SE	(0.052)	(0.035)	(0.040)	(0.043)	(0.037)	(0.045)	(0.058)	(0.033)	(0.068)	(0.033)
P-value of diff.	[0.270]		[0.799]		[0.358]		[0.667]		[0.681]	
Panel E. Number of job applications in past 7 days (N); from job search surveys										
N	1,748	1,539	1,691	1,456	1,748	1,539	1,748	1,539	1,700	1,457
Control mean	5.94	3.38	3.45	5.45	2.91	6.45	3.83	4.41	3.10	4.65
Treatment effect	0.621	3.64**	3.18	1.94	2.26	3.49	0.580	3.93*	2.73	2.06
SE	(4.06)	(1.82)	(2.69)	(2.26)	(1.97)	(3.19)	(2.71)	(2.24)	(4.88)	(1.67)
P-value of diff.	[0.620]		[0.650]		[0.810]		[0.314]		[0.806]	

Notes: This table reports heterogeneity in local average treatment effects (LATE) on select outcomes across sample subgroups defined by baseline characteristics. Treatment take-up is defined as spending at least 10 minutes on the NextUp Jobs website. The employed/not employed subgroups are defined using data from the baseline survey. The "above p75 earnings in Q-1" subgroup contains participants who had UI earnings above the 75th percentile of the sample in the quarter prior to their study enrollment. All estimates are from a two-stage least squares regression using the person's assigned treatment status as an instrument for take-up. The treatment effects in panels C, D, and E adjust for the following self-reported characteristics from the baseline survey: age at enrollment, race, sex, currently employed (y/n), and highest education. The effects in panels A and B additionally adjust for the outcome measured in each of the four complete quarters prior to the person's study enrollment date. The bracketed numbers are the p-values of the differences in treatment effects between the two subgroups on either side of the bracketed number. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

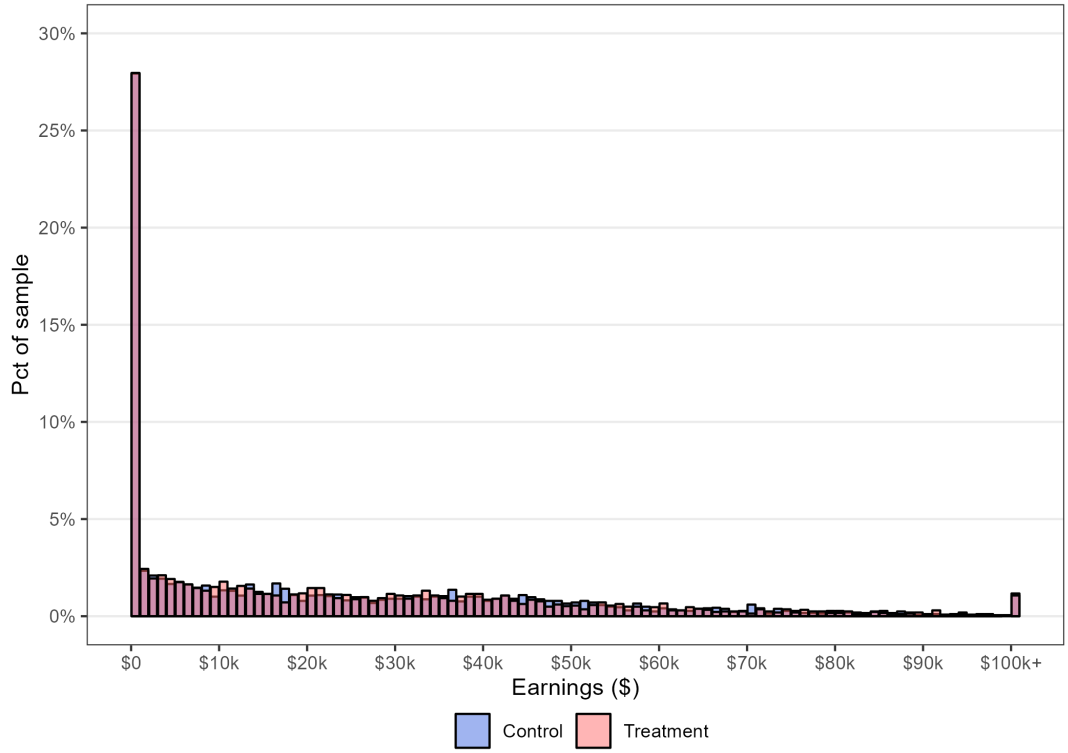
Figures

Figure 1: Total time spent on NextUp Jobs website, among treatment group members who visited the site at least once



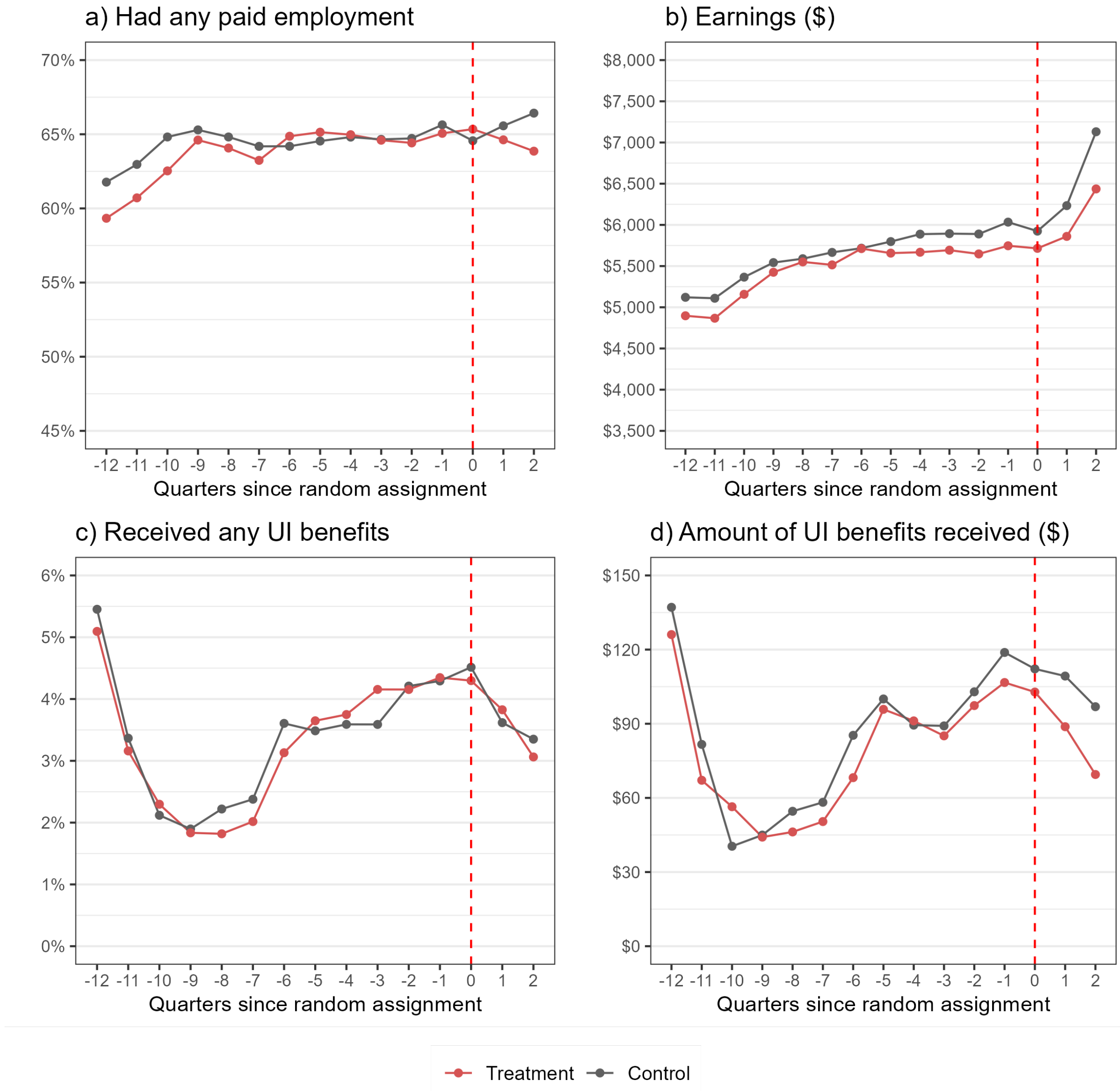
Notes: Figure shows the distribution of the total amount of time that treatment group members have spent on the NextUp Jobs website, only among the participants who visited the site at least once. Bars represent binned increments of 2 minutes.

Figure 2: Participants' total UI earnings in the first four quarters prior to enrollment



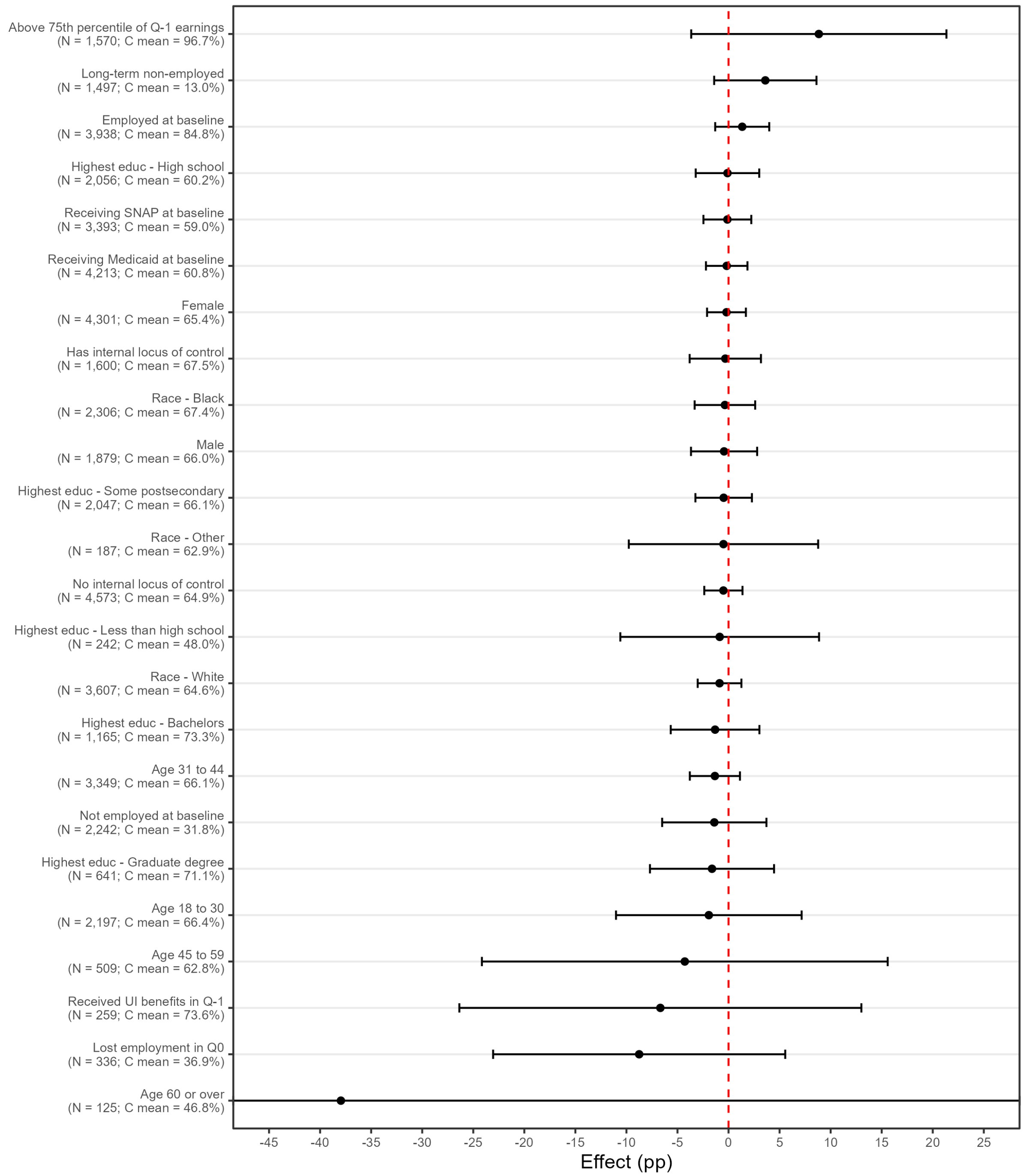
Notes: Figure shows the distribution of study participants' total earnings in the first four calendar quarters prior to the quarter in which they joined the study. Bars represent binned increments of $1,000.

Figure 3: Raw employment outcomes over time relative to random assignment



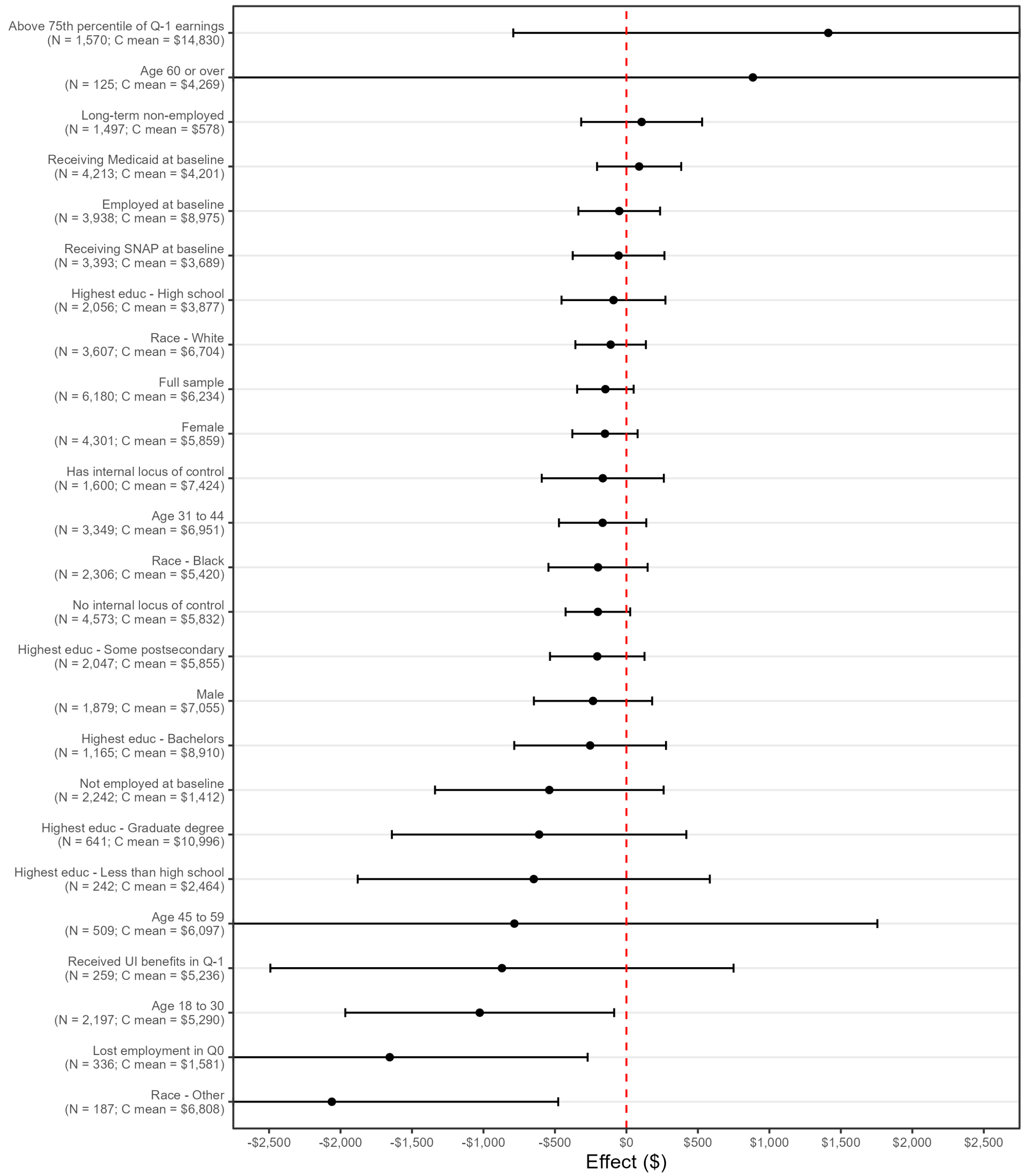
Notes: Figures show mean quarterly employment outcomes over time relative to the calendar quarter in which the person was randomly assigned. The means in panels B and D include values of zero.

Figure 4: Intent-to-treat effects on employment in first full quarter after study enrollment, by baseline subgroups



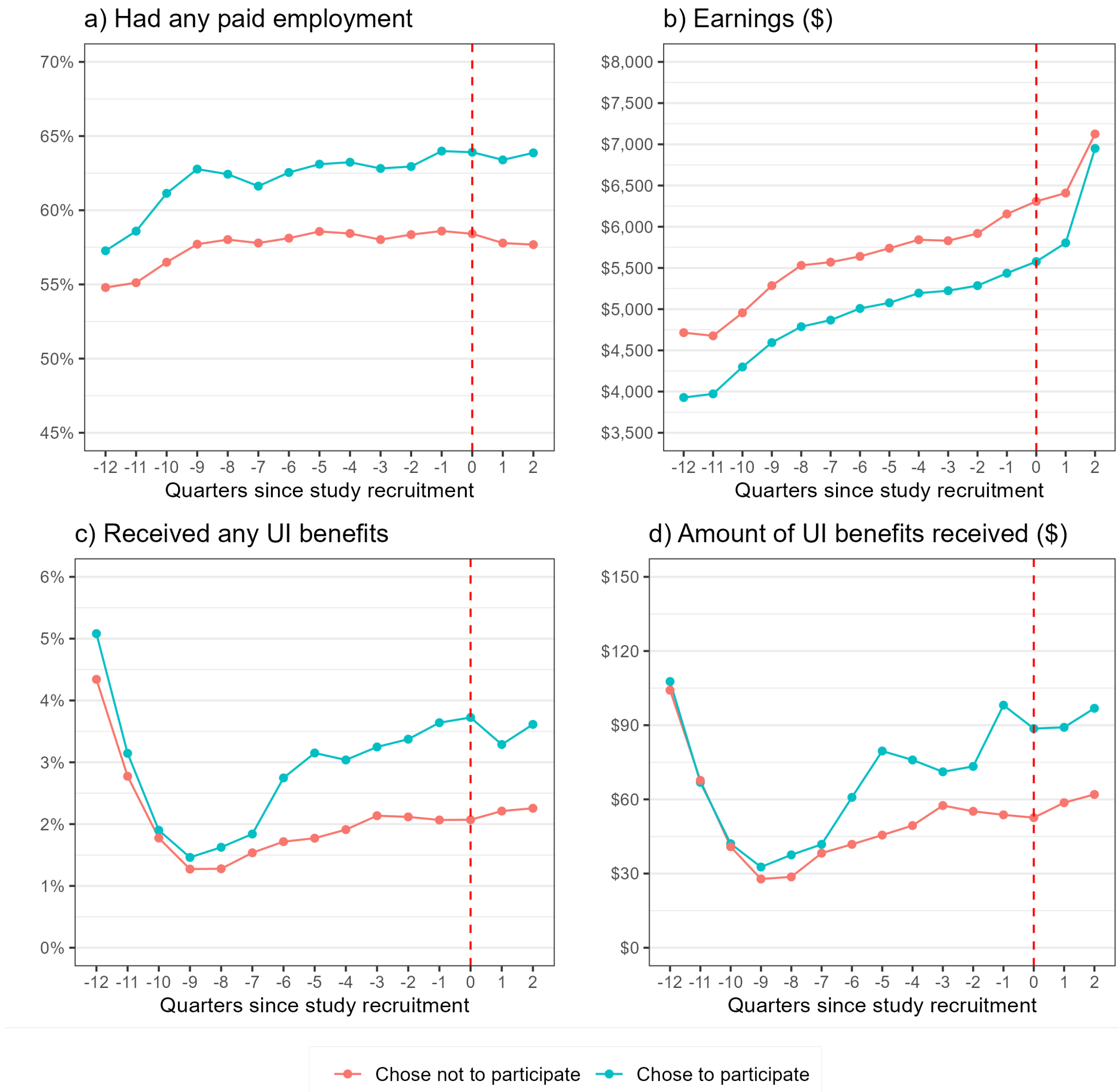
Notes: Figure shows heterogeneity in the intent-to-treat effect on Q1 employment across sample subgroups defined by baseline characteristics. All estimates adjust for the following baseline covariates (omitting those that are colinear with the given subgroup): age at enrollment, race, sex, currently employed (y/n), highest education, and employment in the four quarters prior to enrollment.

Figure 5: Intent-to-treat effects on earnings in first full quarter after study enrollment, by baseline subgroups



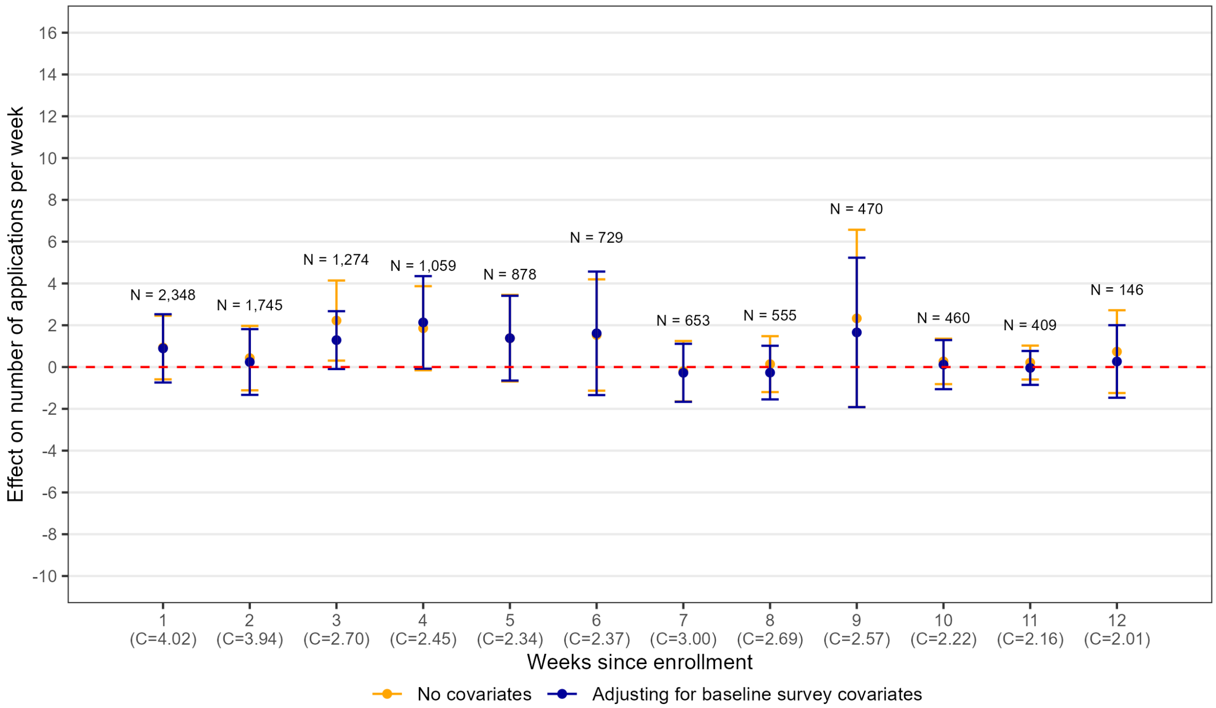
Notes: Figure shows heterogeneity in the intent-to-treat effect on Q1 earnings across sample subgroups defined by baseline characteristics. All estimates adjust for the following baseline covariates (omitting those that are colinear with the given subgroup): age at enrollment, race, sex, currently employed (y/n), highest education, and earnings in the four quarters prior to enrollment.

Figure 6: Raw employment outcomes over time relative to recruitment outreach, among all individuals who received targeted study recruitment



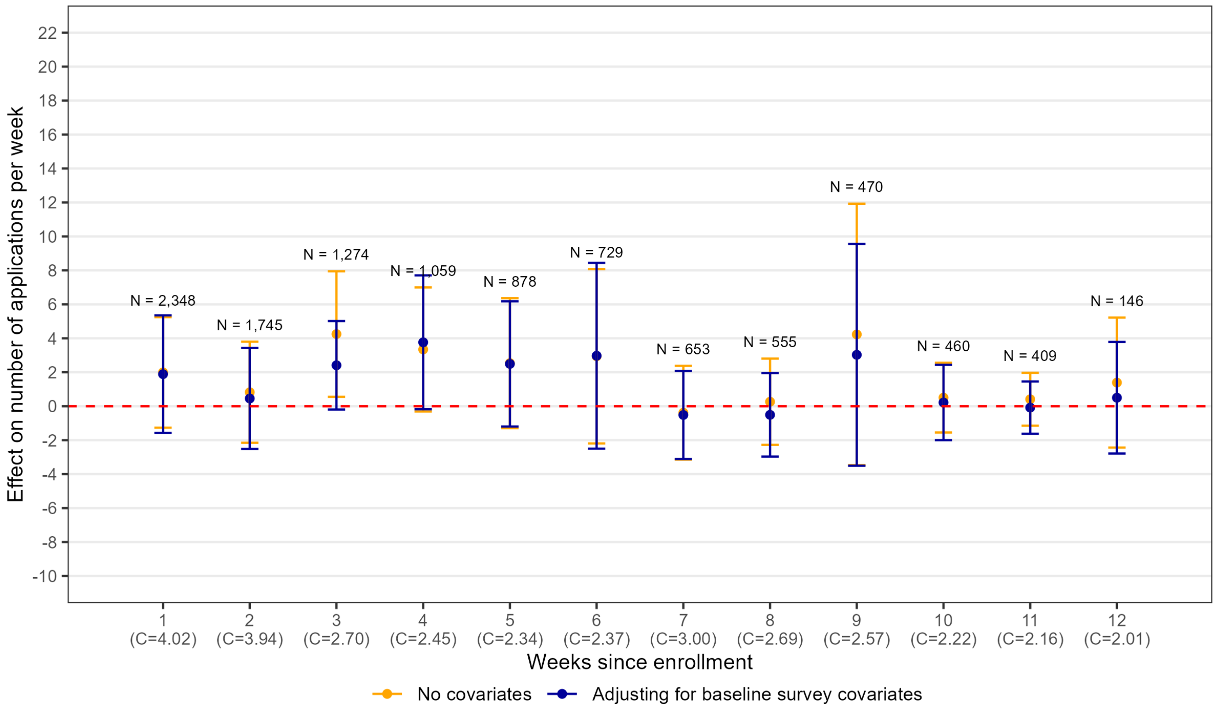
Notes: Figures show mean quarterly employment outcomes among all individuals who were contacted directly by the Allegheny County Department of Human Services (ACDHS) with an offer to join the study. Outcomes are measured over time relative to the calendar quarter in which the person received the targeted recruitment message. The means in panels B and D include values of zero.

Figure 7: Intent-to-treat effects on number of jobs applied to per week, from weekly job search diaries



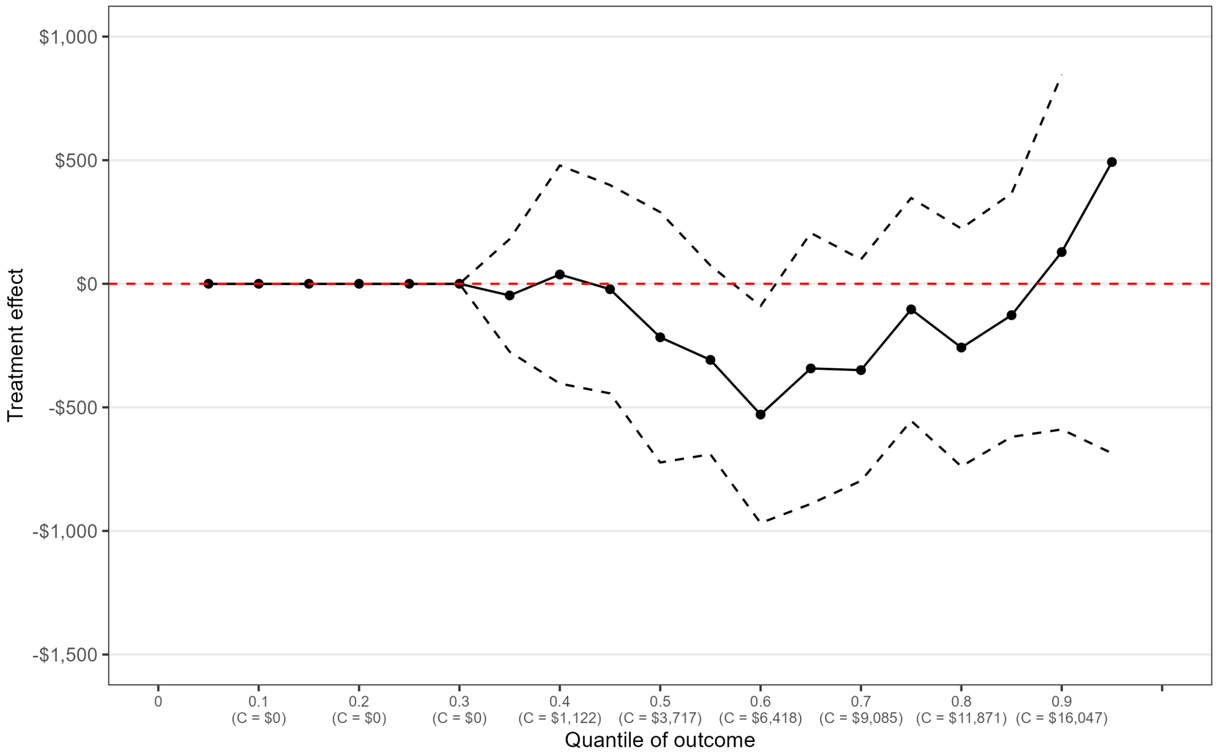
Notes: Figure shows the effect of being assigned to the treatment group on the number of job applications that participants applied to per week relative to the person's date of study enrollment. Data on job applications is self-reported and comes from the weekly text message job search diary surveys. The labels above each treatment effect indicate the number of participants that answered the question about job applications in the given week. The labels below the weeks on the x-axis indicate the mean number of job applications among the control group. The covariate-adjusted estimates control for the following self-reported characteristics from the baseline survey: age at enrollment, race, sex, currently employed (y/n), and highest education. Error bars are 95% confidence intervals using robust standard errors.

Figure 8: Effect of spending at least 10 minutes on the NextUp Jobs website on number of jobs applied to per week, from weekly job search diaries



Notes: Figure shows the effect of spending at least 10 minutes on the NextUp Jobs website on the number of job applications that participants applied to per week, relative to the person's date of study enrollment. Data on job applications is self-reported and comes from the weekly text message job search diary surveys. The labels above each treatment effect indicate the number of participants that answered the question about job applications in the given week. The labels below the weeks on the x-axis indicate the mean number of job applications among the control group. Estimates are from a two-stage least squares regression using the person's assigned treatment status as an instrument for spending at least 10 minutes on the website. The covariate-adjusted estimates control for the following self-reported characteristics from the baseline survey: age at enrollment, race, sex, currently employed (y/n), and highest education. Error bars are 95% confidence intervals using robust standard errors.

Figure 9: Intent-to-treat effects on quantiles of the distribution of earnings in first full quarter after study enrollment



Notes: Figure presents estimates of the effect of being assigned to the treatment group on quantiles of earnings in the first full calendar quarter after study enrollment. Estimates adjust for the following baseline covariates: Age at enrollment, race, sex, currently employed (y/n), highest education, and earnings in the four quarters before the person enrolled in the study. The x-axis labels report the quantile value for the control group. Dashed lines represent 95% confidence intervals using bootstrapped standard errors.

Imperfect Information and the Labor Market: Evidence from Allegheny County

Online Appendix

Alex Bartik, Seth Chizeck, and Bryan Stuart

A Additional tables and figures

Table A1: Baseline sample characteristics for control subjects who received job search diaries and control subjects who did not receive diaries

	Diary-eligibles	Diary-ineligibles	Std. diff.	p-value
Panel A. Demographics				
Age (years)	36.75	36.65	0.010	0.843
Sex				
Female	0.803	0.803	0.001	0.980
Male	0.183	0.179	0.009	0.856
Other	0.014	0.018	-0.032	0.530
Race				
Black	0.453	0.452	0.002	0.967
White	0.534	0.515	0.037	0.472
Other	0.013	0.033	-0.132	0.013
Highest education				
Less than high school	0.044	0.039	0.022	0.661
High school	0.357	0.376	-0.040	0.430
Some postsecondary schooling	0.384	0.364	0.042	0.408
Bachelors degree	0.147	0.130	0.050	0.327
Graduate degree	0.064	0.088	-0.093	0.070
Lives in Allegheny County, PA	0.936	0.930	0.025	0.619
Panel B. Received public benefits in the 12 months prior to enrollment				
Medicaid	0.749	0.731	0.040	0.429
SNAP	0.692	0.674	0.039	0.452
TANF	0.079	0.082	-0.009	0.863
SSI	0.044	0.034	0.049	0.339
Panel C. Employment status and beliefs				
Currently employed	0.602	0.596	0.012	0.807
I would benefit from using a job search tool	0.642	0.662	-0.044	0.386
I know what types of jobs are good matches	0.782	0.798	-0.040	0.425
It would be difficult to find a better job	0.294	0.289	0.011	0.825
Panel D. Employment in the calendar quarter prior to enrollment				
Had any paid employment	0.644	0.666	-0.046	0.371
Total earnings ($; includes zeroes)	5,846	5,810	0.004	0.943
Received unemployment benefits	0.046	0.051	-0.025	0.637
Test for joint orthogonality				
F-stat	1.246			
p-value	0.190			
Total sample size	**849**	**715**		

Notes: This table shows mean baseline characteristics for two subsets of the control group: those who were randomly assigned to receive the weekly job search diary surveys and those who were randomly assigned not to receive these surveys. The analysis is limited to control group members who joined the study on or after December 9, 2024, which is when we began randomizing diary eligibility among the control group. The ‘std. diff’ column reports the standardized mean difference between the two groups. The variables in panels A and C come from the baseline survey. The variables in panel B come from administrative records from the Allegheny County Department of Human Services (ACDHS). The variables in panel D come from Pennsylvania unemployment insurance (UI) records. The omnibus test for joint orthogonality is calculated using randomization inference.

Table A2: Differences in outcomes for control subjects who received job search diaries versus control subjects who did not receive diaries

Outcome	N	Control mean	(1)	(2)	(3)	(4)
Panel A. Outcomes from UI records						
Had any paid employment	935	0.634	0.018	0.015	0.011	0.014
			(0.031)	(0.023)	(0.020)	(0.022)
Earnings ($)	935	5,460	-198.5	-150.5	-90.29	-143.2***
			(433.1)	(273.6)	(222.6)	(247.8)
Received UI benefits	935	0.044	-0.015	-0.006	-0.016	-0.014
			(0.012)	(0.012)	(0.012)	(0.012)
Amount of UI benefits received ($)	935	145.6	-61.86	-24.99	-61.00	-62.21***
			(47.51)	(41.72)	(47.21)	(46.79)
Panel B. Outcomes from endline survey						
Currently employed	948	0.642	-0.047	-0.056**	-0.057**	-0.050
			(0.032)	(0.027)	(0.023)	(0.024)
What happens to me is my own doing, OR Sometimes I feel that I don't have enough control over the direction my life is taking	925	0.556	0.037	0.037	0.030	0.030
			(0.033)	(0.036)	(0.029)	(0.030)
Life satisfaction (0-10 scale)	921	5.93	0.189	0.159	0.191	0.166
			(0.161)	(0.174)	(0.142)	(0.146)
Could not pay a $400 emergency expense	922	0.441	0.045	0.053	0.023	0.035
			(0.033)	(0.033)	(0.028)	(0.029)
Able to pay all bills in full this month	922	0.436	-0.059*	-0.070**	-0.048*	-0.055
			(0.032)	(0.035)	(0.026)	(0.027)
Felt anxious on more than half the days during the past 2 weeks (%)	920	0.364	-0.001	-0.007	<0.001	<0.001
			(0.032)	(0.035)	(0.028)	(0.029)
Adjusts for benchmark covariates				X		
Post-double LASSO covariate selection					X	
Causal forest						X

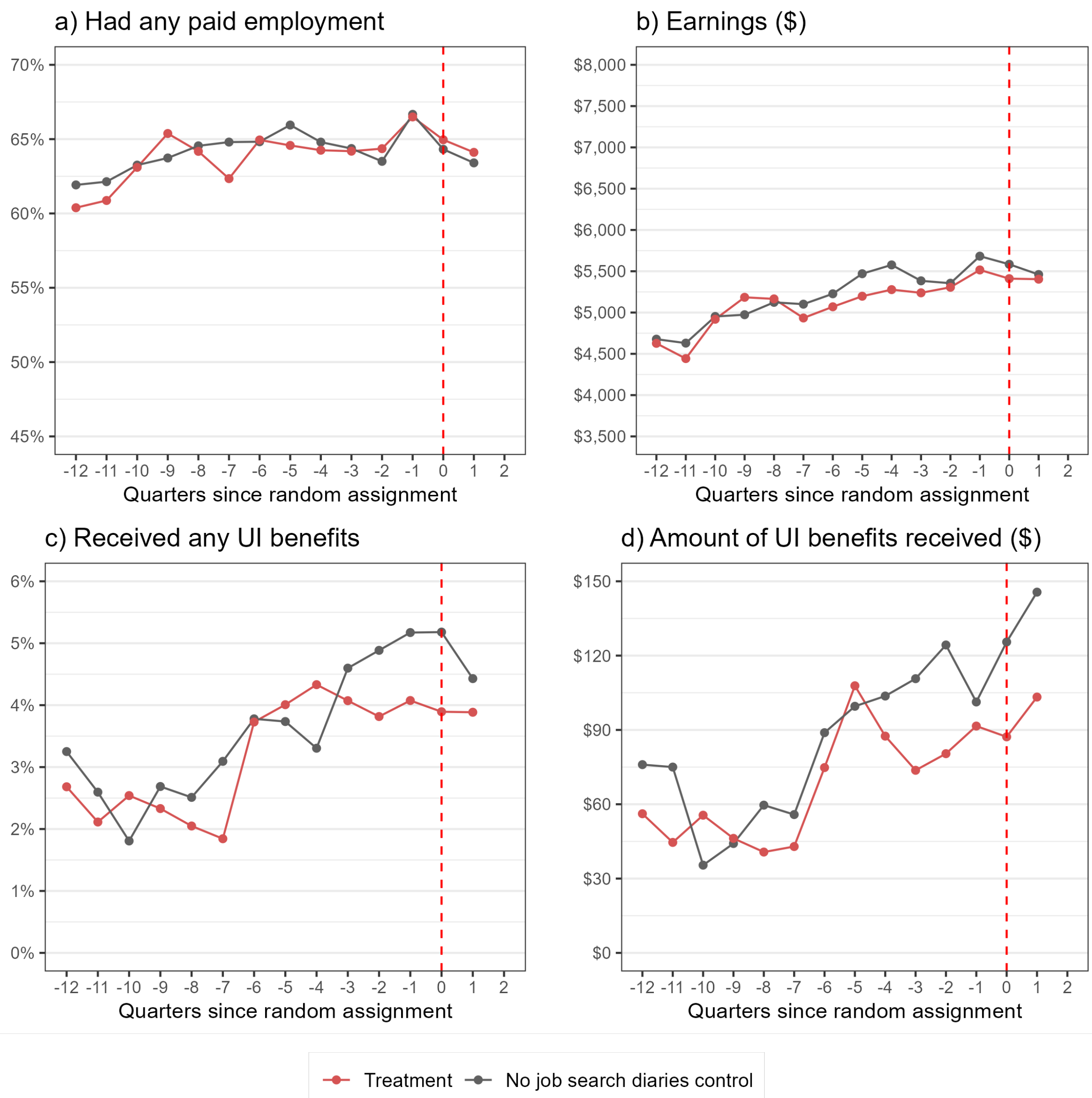
Notes: Table compares mean outcomes for two subsets of the control group: those who were randomly assigned to receive the weekly job search diary surveys and those who were randomly assigned not to receive these surveys. The analysis is limited to control group members who joined the study on or after December 9, 2024, which is when we began randomizing diary eligibility among the control group. Column (1) regresses the outcome on an indicator for being eligible to receive the job search surveys, with no covariates. Column (2) adjusts for the following baseline covariates: age at enrollment, race, sex, currently employed (y/n), highest education, and the outcome measured in the four quarters prior to enrollment (only in panel A). Column (3) selects covariates using post-double LASSO. Column (4) estimates the treatment effect nonparametrically using machine learning causal forests. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A3: Selection into study participation among those who received targeted recruitment outreach

	Chose to participate	Chose not to participate	Difference
Panel A. Demographics			
Age (years)	30.64	30.81	-0.175** (0.087)
Female	0.637	0.489	0.147*** (0.006)
Race - Black	0.396	0.304	0.091*** (0.006)
Race - White	0.574	0.656	-0.082*** (0.006)
Race - Other	0.030	0.039	-0.009*** (0.002)
Panel B. Received public benefits in the 12 months prior to recruitment			
Medicaid	0.681	0.475	0.206*** (0.006)
SNAP	0.529	0.283	0.246*** (0.006)
TANF	0.047	0.016	0.031*** (0.003)
SSI	0.042	0.034	0.008*** (0.002)
Panel C. Employment in the calendar quarter prior to recruitment			
Had any paid employment	0.639	0.585	0.054*** (0.006)
Total earnings ($; includes zeroes)	5,424	6,150	-725.6*** (91.58)
Received unemployment benefits	0.036	0.021	0.016*** (0.002)
N	**7,226**	**213,844**	

Notes: This table shows the mean characteristics of the individuals who were contacted directly by the Allegheny County Department of Human Services (ACDHS) with an offer to join the study. The variables in panels A and B come from ACDHS administrative records. The variables in panel C come from Pennsylvania unemployment insurance (UI) records. The standard errors of the unadjusted mean differences are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Figure A1: Raw employment outcomes over time relative to random assignment, treatment group versus job search diary-ineligible control group

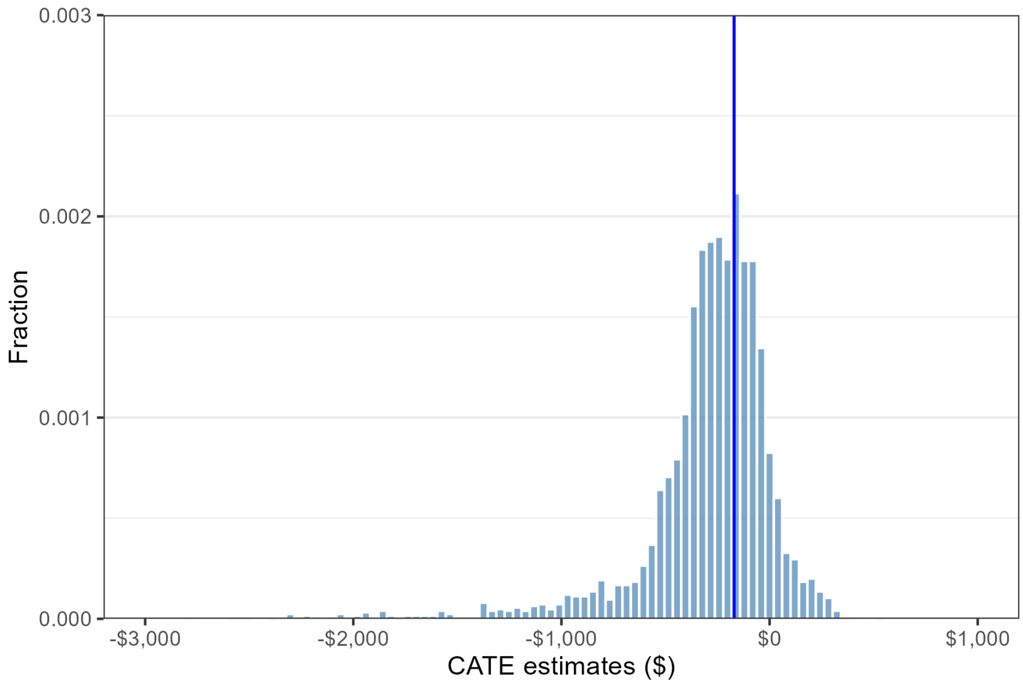


Notes: Figures show mean quarterly employment outcomes over time relative to the calendar quarter in which the person was randomly assigned. The data is limited to participants in the treatment group and the subset of the control group that was randomly assigned to not receive the job search diary surveys. Data is also limited to participants who entered the study on or after December 9, 2024 (the date when we began randomizing the control group to receive the job search diaries or not). The means in panels B and D include values of zero.

B Machine learning heterogeneity analysis

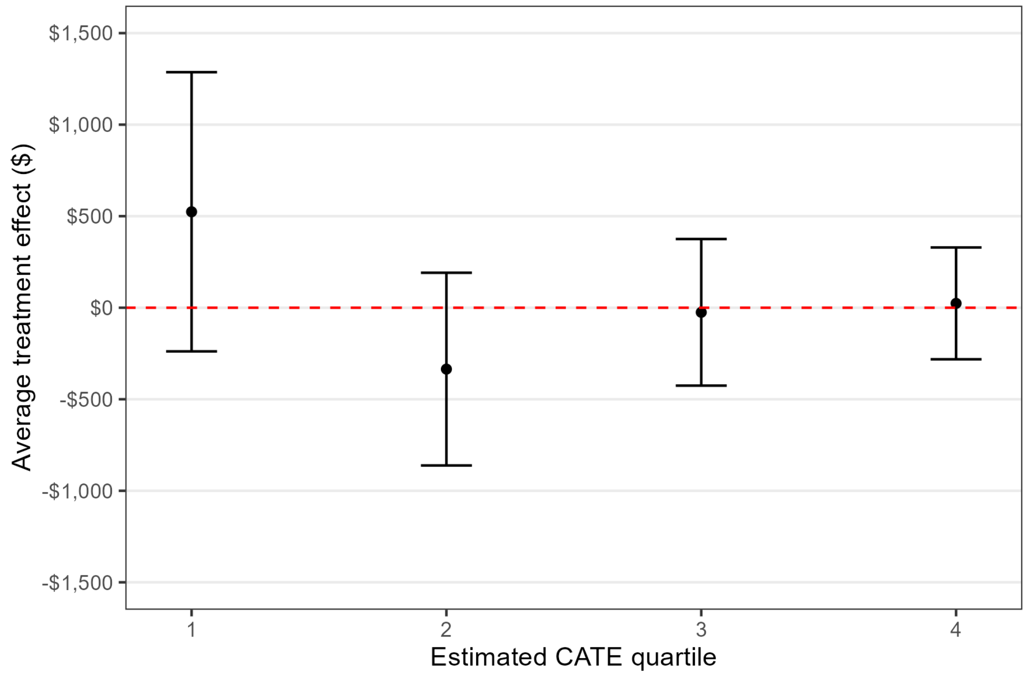
In this section, we explore potential heterogeneous treatment effects on Q1 earnings using machine learning methods. We implement the methods using the 'grf' package in R. We use the default package parameters, which are: number of trees = 2000, fraction of data sampled into each tree = 0.5, number of variables randomly available for each split = $\sqrt{\text{Total number of x variables}} + 20$, minimum leaf size = 5 treated and 5 control units, fraction of sample used for determining splits = 0.5, prune leaves which end up empty when determining treatment effects = TRUE, maximum split imbalance = 0.05, soft imbalance penalty = 0.

Figure B1: Distribution of Conditional Average Treatment Effects (CATE's) on Q1 earnings



Notes: Figure shows the distribution of conditional average treatment effects (CATE's) on earnings in the first full quarter after random assignment.

Figure B2: Average treatment effects by quartiles of the CATE's on Q1 earnings



Notes: Figure shows average treatment effects on Q1 earnings within each quartile of the test set CATE estimates.

Table B1: Mean baseline characteristics of those in top versus bottom quartile of CATE on Q1 earnings

	Top CATE quartile	Bottom CATE quartile	Difference	Standard error	p-value
Panel A. Demographics					
Age (years)	38.82	38.76	0.059	0.645	0.927
Sex					
Female	0.742	0.780	-0.038	0.029	0.189
Male	0.247	0.217	0.030	0.029	0.291
Other	0.011	0.003	0.008	0.005	0.131
Race					
Black	0.371	0.383	-0.012	0.033	0.712
White	0.607	0.593	0.014	0.034	0.687
Other	0.022	0.023	-0.001	0.010	0.902
Highest education					
Less than high school	0.081	0.000	0.081	0.010	<0.001
High school	0.419	0.138	0.281	0.027	<0.001
Some postsecondary schooling	0.321	0.289	0.032	0.031	0.313
Bachelors degree	0.096	0.316	-0.220	0.029	<0.001
Graduate degree	0.072	0.253	-0.181	0.027	<0.001
Lives in Allegheny County, PA	0.941	0.938	0.004	0.016	0.819
Panel B. Received public benefits in the 12 months prior to enrollment					
Medicaid	0.822	0.378	0.444	0.031	<0.001
SNAP	0.730	0.267	0.463	0.030	<0.001
TANF	0.081	0.026	0.054	0.014	<0.001
SSI	0.082	0.000	0.082	0.010	<0.001
Panel C. Employment status and beliefs					
Currently employed	0.346	0.905	-0.559	0.024	<0.001
I would benefit from using a job search tool	0.563	0.655	-0.091	0.033	0.006
I know what types of jobs are good matches	0.749	0.838	-0.089	0.027	<0.001
It would be difficult to find a better job	0.252	0.304	-0.052	0.031	0.096
Panel D. Employment in the calendar quarter prior to enrollment					
Had any paid employment	0.268	0.970	-0.703	0.019	<0.001
Total earnings ($; includes zeroes)	1,350	17,312	-15,962	483.8	<0.001
Received unemployment benefits	0.016	0.036	-0.020	0.012	0.091

Notes: This table shows mean baseline characteristics for the study participants who are in the top versus bottom quartile of conditional average treatment effects (CATE's) on earnings in the first full quarter after random assignment. The standard errors of the mean differences are calculated from an OLS regression of the characteristic on an indicator for being in the top (versus bottom) CATE quartile. The variables in panels A and C come from the baseline survey. The variables in panel B come from administrative records from the Allegheny County Department of Human Services (ACDHS). The variables in panel D come from Pennsylvania unemployment insurance (UI) records.

C Survey nonresponse

C.1 Endline survey

Table C1: Endline survey response rates

Survey question	Overall	Treatment	Control	T/C diff.
Currently employed	0.547	0.503	0.589	-0.086*** (0.011)
Current or prior occupation	0.539	0.498	0.581	-0.083*** (0.011)
Agrees with the following statement (%)				
I have a good idea of the types of jobs that are good matches for me	0.539	0.498	0.581	-0.083*** (0.011)
It would be difficult for me to find a better job given my current education and work experience	0.539	0.498	0.581	-0.083*** (0.011)
My local government tries to improve opportunities for people like me	0.539	0.498	0.581	-0.083*** (0.011)
Agrees with the statement with stronger internal locus of control (%)				
What happens to me is my own doing, OR Sometimes I feel that I don't have enough control over the direction my life is taking	0.537	0.496	0.577	-0.081*** (0.011)
When I make plans, I am almost certain that I can make them work, OR It is not always wise to plan too far ahead because many things turn out to be a matter of good or bad fortune	0.537	0.496	0.577	-0.081*** (0.011)
In my case getting what I want has little or nothing to do with luck, OR Many times we might just as well decide what to do by flipping a coin	0.537	0.496	0.577	-0.081*** (0.011)
Many times I feel that I have little influence over the things that happen to me, OR It is impossible for me to believe that chance or luck plays an important role in my life	0.537	0.496	0.577	-0.081*** (0.011)
Life satisfaction (0-10 scale)	0.535	0.495	0.575	-0.080*** (0.011)
Could not pay a $400 emergency expense	0.536	0.496	0.576	-0.080*** (0.011)
Able to pay all bills in full this month	0.536	0.496	0.576	-0.080*** (0.011)
Bothered by the following on more than half the days during the past 2 weeks (%)				
Feeling nervous, anxious, or on edge	0.535	0.495	0.575	-0.080*** (0.011)
Not able to stop or control worrying	0.535	0.495	0.575	-0.080*** (0.011)
Little interest or pleasure in doing things	0.535	0.495	0.575	-0.080*** (0.011)
Feel down, depressed, or hopeless	0.535	0.495	0.575	-0.080*** (0.011)
Completed the survey	**0.534**	**0.494**	**0.574**	**-0.079*** (0.011)**

Notes: Table presents the response rates to the endline survey questions. Response rates vary across questions because some questions did not force a response and partially-completed surveys were recorded after being inactive for one month. The final question in the survey asked respondents to check a box to indicate that they have completed the survey. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table C2: Selection into endline survey completion on baseline characteristics

	Completers	Non-completers	Difference
Panel A. Demographics			
Age (years)	34.61	35.30	-0.683*** (0.223)
Sex			
Female	0.712	0.669	0.043*** (0.011)
Male	0.273	0.314	-0.041*** (0.010)
Other	0.015	0.017	-0.002 (0.003)
Race			
Black	0.386	0.387	-0.002 (0.011)
White	0.585	0.584	0.001 (0.012)
Other	0.029	0.029	<0.001 (0.004)
Highest education			
Less than high school	0.038	0.041	-0.003 (0.004)
High school	0.329	0.350	-0.022** (0.011)
Some postsecondary schooling	0.342	0.332	0.010 (0.011)
Bachelors degree	0.182	0.174	0.007 (0.009)
Graduate degree	0.107	0.097	0.010 (0.007)
Panel B. Received public benefits in the 12 months prior to enrollment			
Medicaid	0.679	0.650	0.029*** (0.011)
SNAP	0.578	0.556	0.022* (0.012)
TANF	0.060	0.050	0.010* (0.005)
SSI	0.039	0.037	0.003 (0.004)
Panel C. Employment status and beliefs			
Currently employed	0.636	0.624	0.012 (0.011)
I would benefit from using a job search tool	0.681	0.654	0.027** (0.011)
I know what types of jobs are good matches	0.801	0.783	0.018* (0.009)
It would be difficult to find a better job	0.308	0.297	0.011 (0.011)
Panel D. Employment in the calendar quarter prior to enrollment			
Had any paid employment	0.658	0.649	0.009 (0.011)
Total earnings ($; includes zeroes)	5,811	5,984	-173.57 (187.2)
Received unemployment benefits	0.046	0.039	0.007 (0.005)
N	**4,075**	**3,552**	

Notes: This table compares the mean baseline characteristics of the endline survey completers and non-completers. The final question in the survey asked participants to check a box to indicate that they have completed the survey. In this table, we consider a participant to have completed the survey if they checked this box, regardless of how many questions they answered within the survey (not all questions forced a response). Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table C3: Randomization balance among endline survey respondents

	Treatment	Control	Std. diff.	p-value
Panel A. Demographics				
Age (years)	34.47	34.74	-0.029	0.362
Sex				
Female	0.731	0.695	0.078	0.012
Male	0.256	0.288	-0.072	0.021
Other	0.013	0.017	-0.028	0.369
Race				
Black	0.394	0.378	0.033	0.310
White	0.572	0.597	-0.050	0.119
Other	0.034	0.025	0.052	0.106
Highest education				
Less than high school	0.044	0.032	0.066	0.037
High school	0.348	0.312	0.075	0.017
Some postsecondary schooling	0.331	0.352	-0.045	0.153
Bachelors degree	0.174	0.188	-0.035	0.260
Graduate degree	0.101	0.112	-0.037	0.235
Lives in Allegheny County, PA	0.968	0.961	0.037	0.230
Panel B. Received public benefits in the 12 months prior to enrollment				
Medicaid	0.705	0.657	0.103	0.001
SNAP	0.598	0.561	0.075	0.019
TANF	0.068	0.054	0.057	0.077
SSI	0.041	0.038	0.016	0.613
Panel C. Employment status and beliefs				
Currently employed	0.634	0.639	-0.010	0.741
I would benefit from using a job search tool	0.676	0.684	-0.017	0.582
I know what types of jobs are good matches	0.789	0.812	-0.057	0.070
It would be difficult to find a better job	0.307	0.308	-0.003	0.932
Panel D. Employment in the calendar quarter prior to enrollment				
Had any paid employment	0.654	0.661	-0.013	0.685
Total earnings ($; includes zeroes)	5,516	6,063	-0.077	0.015
Received unemployment benefits	0.047	0.046	<0.001	0.976
Test for joint orthogonality				
F-stat	1.180			
p-value	0.270			
Total sample size	**1,872**	**2,205**		

Notes: This table shows mean baseline characteristics for the treatment and control group members who completed the endline survey. The final question in the survey asked participants to check a box to indicate that they have completed the survey. In this table, we consider a participant to have completed the survey if they checked this box, regardless of how many questions they answered within the survey (not all questions forced a response). The 'std. diff' column reports the standardized mean difference between the two groups. The variables in panels A and C come from the baseline survey. The variables in panel B come from administrative records from the Allegheny County Department of Human Services (ACDHS). The variables in panel D come from Pennsylvania unemployment insurance (UI) records. The omnibus test for joint orthogonality is calculated using randomization inference.

Table C4: Intent-to-treat effects on administrative employment outcomes, by endline survey completion

	Completed endline		Did not complete endline
Panel A. Had any paid employment in Q1 after enrollment; from UI records			
N	3,084		3,096
Control mean	0.668		0.639
Treatment effect	-0.023**		0.021*
SE	(0.012)		(0.012)
P-value of diff.		[0.012]	
Panel B. Earnings in Q1 after enrollment $); from UI records			
N	3,084		3,096
Control mean	6,247		6,216
Treatment effect	-148.6		-167.5
SE	(130.7)		(157.1)
P-value of diff.		[0.834]	

Notes: This table presents intent-to-treat effects on employment outcomes measured from administrative UI records, disaggregated by whether the person completed the endline survey. The final question in the survey asked participants to check a box to indicate that they have completed the survey. In this table, we consider a participant to have completed the survey if they checked this box, regardless of how many questions they answered within the survey (not all questions forced a response). The treatment effects adjust for: age at enrollment, race, sex, currently employed (y/n), highest education, and the outcome measured in each of the four complete quarters prior to the person's study enrollment date. The bracketed numbers are the p-values of the differences in treatment effects between the two subgroups on either side of the bracketed number. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

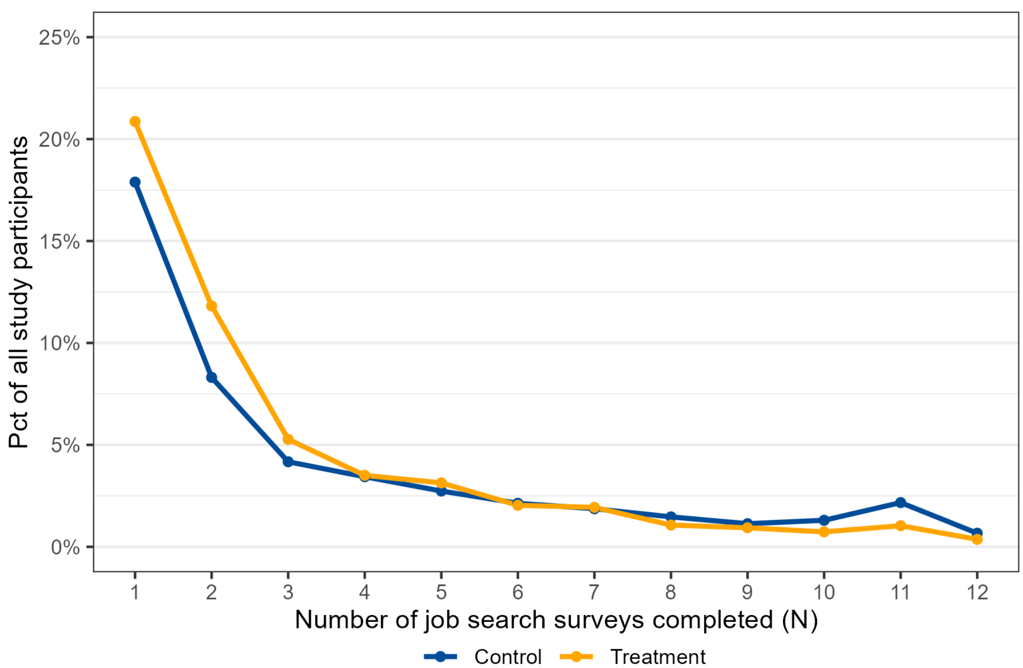
C.2 Job search surveys

Table C5: Job search survey response rates

	Overall	Treatment	Control	T/C diff.
Completed at least 1 job search survey	0.433	0.417	0.453	-0.036*** (0.012)
Number of surveys completed (out of 12), among those who completed at least 1	3.23	2.96	3.54	-0.578*** (0.106)

Notes: Table presents the response rates to the text message job search surveys. Participants received these surveys on a weekly basis for the first 12 weeks after joining the study. In this table, we consider a participant to have responded to a survey if they answered every question in the survey. The analysis excludes the 715 participants who were randomly excluded from receiving the job search diaries. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Figure C1: Distribution of number of job search surveys completed, among those who completed at least one



Notes: Figure presents the distribution of the number of text message job search surveys that each participant completed. Participants received these surveys on a weekly basis for the first 12 weeks after joining the study. In this figure, we consider a participant to have completed a survey if they answered every question in the survey. The analysis excludes the 715 participants who were randomly excluded from receiving the job search diaries.

Table C6: Selection into job search survey completion on baseline characteristics

	Completers	Non-completers	Difference
Panel A. Demographics			
Age (years)	34.94	34.61	0.329 (0.232)
Sex			
Female	0.684	0.678	0.006 (0.011)
Male	0.301	0.306	-0.005 (0.011)
Other	0.015	0.016	-0.001 (0.003)
Race			
Black	0.379	0.380	-0.001 (0.012)
White	0.597	0.588	0.010 (0.012)
Other	0.024	0.032	-0.008** (0.004)
Highest education			
Less than high school	0.037	0.041	-0.004 (0.005)
High school	0.308	0.355	-0.047*** (0.011)
Some postsecondary schooling	0.353	0.321	0.032*** (0.011)
Bachelors degree	0.190	0.178	0.012 (0.009)
Graduate degree	0.109	0.100	0.009 (0.007)
Panel B. Received public benefits in the 12 months prior to enrollment			
Medicaid	0.660	0.657	0.003 (0.012)
SNAP	0.561	0.554	0.007 (0.012)
TANF	0.051	0.054	-0.004 (0.006)
SSI	0.036	0.040	-0.004 (0.005)
Panel C. Employment status and beliefs			
Currently employed	0.619	0.646	-0.027** (0.012)
I would benefit from using a job search tool	0.695	0.649	0.045*** (0.011)
I know what types of jobs are good matches	0.793	0.792	0.001 (0.010)
It would be difficult to find a better job	0.312	0.298	0.013 (0.011)
Panel D. Employment in the calendar quarter prior to enrollment			
Had any paid employment	0.665	0.641	0.024** (0.012)
Total earnings ($; includes zeroes)	6,003	6,028	-24.77 (197.0)
Received unemployment benefits	0.050	0.036	0.014*** (0.005)
N	**2,996**	**3,916**	

Notes: This table compares the mean baseline characteristics of the participants who completed at least one job search survey with those who did not complete any of these surveys. Participants received these surveys on a weekly basis for the first 12 weeks after joining the study. In this table, we consider a participant to have completed a survey if they answered every question in the survey. The analysis excludes the 715 participants who were randomly excluded from receiving the job search diaries. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table C7: Randomization balance among job search survey respondents

	Treatment	Control	Std. diff.	p-value
Panel A. Demographics				
Age (years)	35.04	34.82	0.024	0.516
Sex				
Female	0.712	0.651	0.132	<0.001
Male	0.273	0.333	-0.131	<0.001
Other	0.015	0.016	-0.008	0.830
Race				
Black	0.393	0.363	0.062	0.096
White	0.583	0.613	-0.061	0.103
Other	0.024	0.024	-0.002	0.957
Highest education				
Less than high school	0.043	0.030	0.071	0.049
High school	0.336	0.277	0.128	<0.001
Some postsecondary schooling	0.336	0.372	-0.076	0.038
Bachelors degree	0.176	0.205	-0.075	0.042
Graduate degree	0.107	0.112	-0.014	0.695
Lives in Allegheny County, PA	0.968	0.975	-0.045	0.212
Panel B. Received public benefits in the 12 months prior to enrollment				
Medicaid	0.701	0.615	0.183	<0.001
SNAP	0.596	0.521	0.152	<0.001
TANF	0.057	0.043	0.064	0.084
SSI	0.040	0.031	0.048	0.191
Panel C. Employment status and beliefs				
Currently employed	0.611	0.627	-0.033	0.361
I would benefit from using a job search tool	0.689	0.701	-0.025	0.486
I know what types of jobs are good matches	0.783	0.803	-0.049	0.183
It would be difficult to find a better job	0.315	0.308	0.017	0.650
Panel D. Employment in the calendar quarter prior to enrollment				
Had any paid employment	0.661	0.671	-0.021	0.577
Total earnings ($; includes zeroes)	5,683	6,369	-0.094	0.013
Received unemployment benefits	0.050	0.050	<0.001	0.980
Test for joint orthogonality				
F-stat	0.660			
p-value	0.880			
Total sample size	**1,579**	**1,417**		

Notes: This table shows mean baseline characteristics for the treatment and control group members who completed at least one job search survey. Participants received these surveys on a weekly basis for the first 12 weeks after joining the study. In this table, we consider a participant to have completed a survey if they answered every question in the survey. The 'std. diff' column reports the standardized mean difference between the two groups. The variables in panels A and C come from the baseline survey. The variables in panel B come from administrative records from the Allegheny County Department of Human Services (ACDHS). The variables in panel D come from Pennsylvania unemployment insurance (UI) records. The omnibus test for joint orthogonality is calculated using randomization inference.

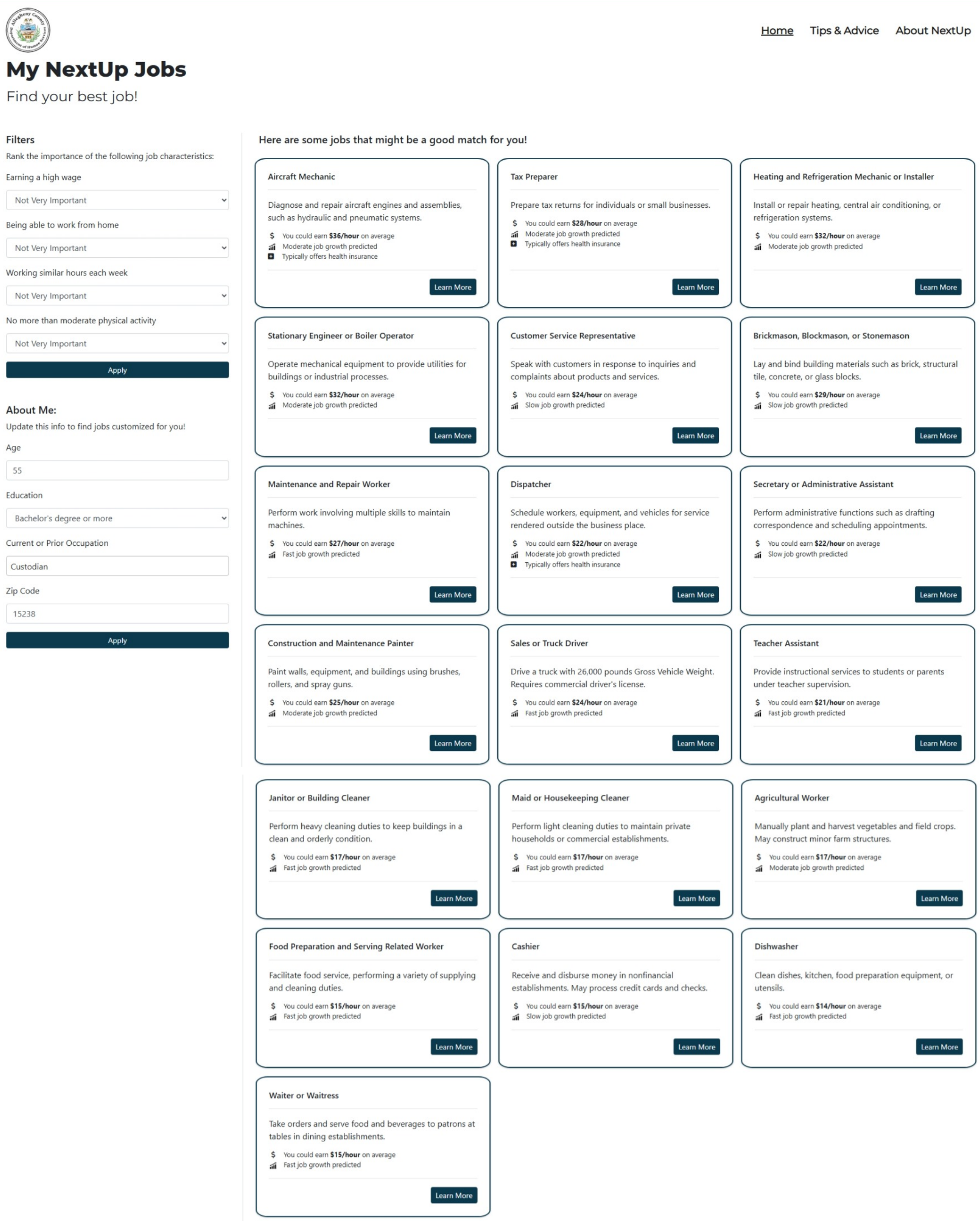
Table C8: Intent-to-treat effects on administrative employment outcomes, by whether the person completed at least one job search diary

	Completed a diary		Did not complete a diary
Panel A. Had any paid employment in Q1 after enrollment; from UI records			
N	1,311		1,375
Control mean	0.705		0.641
Treatment effect	0.018		0.027
SE	(0.022)		(0.019)
P-value of diff.		[0.501]	
Panel B. Earnings in Q1 after enrollment ($); from UI records			
N	1,311		1,375
Control mean	7,608		6,800
Treatment effect	-294.3		-148.5
SE	(270.5)		(225.1)
P-value of diff.		[0.274]	

Notes: This table presents intent-to-treat effects on employment outcomes measured from administrative UI records, disaggregated by whether the person completed at least one job search diary. Participants received these surveys on a weekly basis for the first 12 weeks after joining the study. In this table, we consider a participant to have completed a diary if they answered every question in the diary. The treatment effects adjust for: age at enrollment, race, sex, currently employed (y/n), highest education, and the outcome measured in each of the four complete quarters prior to the person's study enrollment date. The bracketed numbers are the p-values of the differences in treatment effects between the two subgroups on either side of the bracketed number. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

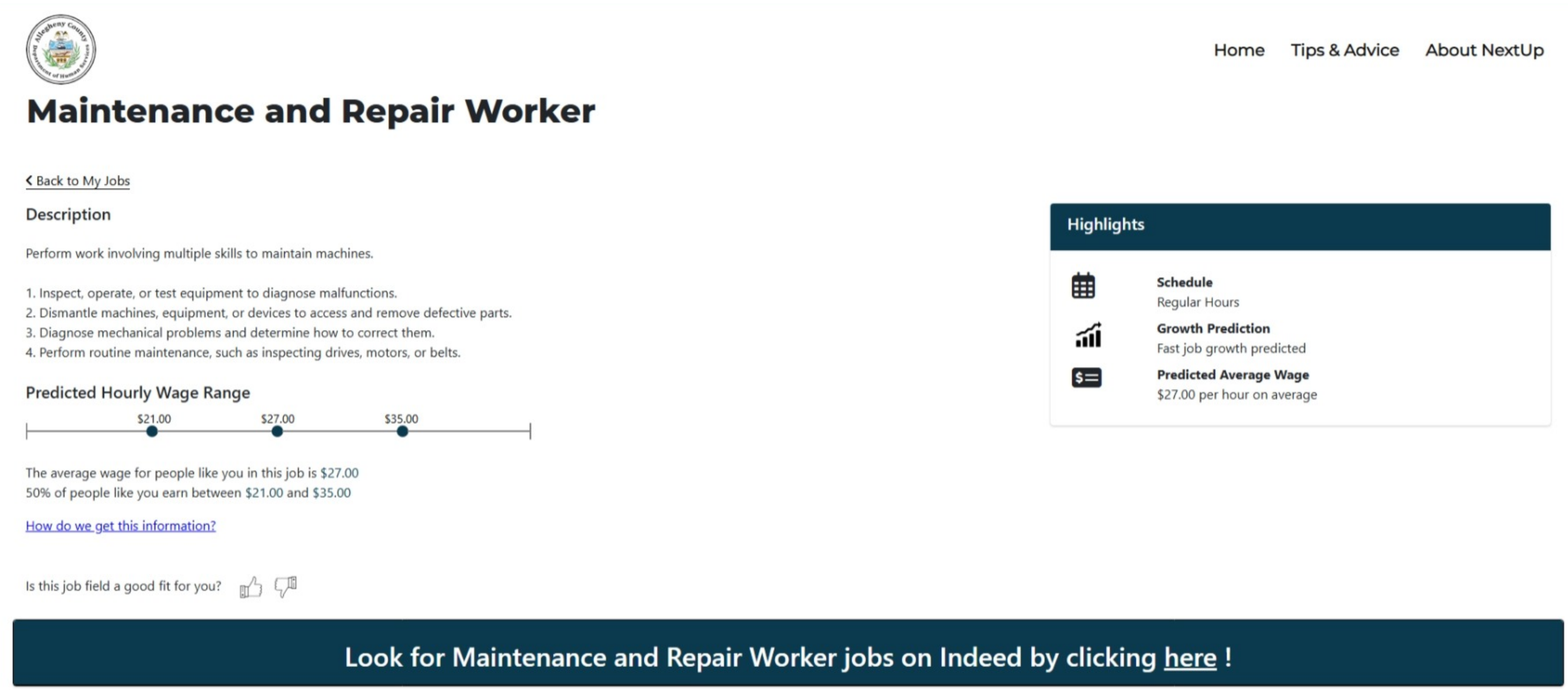
D NextUp Jobs platform screenshots

Figure D1: NextUp Jobs homepage



Notes: Figure shows the homepage of the NextUp Jobs website.

Figure D2: NextUp Jobs homepage



Notes: Figure shows an example page from the NextUp Jobs website that shows more details about an occupation.