Job Search, Overoptimism and Statistical Profiling: Can Information Provision Improve Job Search Outcomes?*

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Abstract

We estimate the causal effect of a large-scale information provision policy targeting unemployed workers in Denmark. The policy aimed to correct overoptimistic beliefs about reemployment prospects. Identification is based on a regression discontinuity design leveraging age discontinuities in the policy's statistical profiling tool. When unemployment insurance recipients are informed that they are at high risk of long-term unemployment, their likelihood of exiting unemployment increases significantly. These exits reflect two very distinct mechanisms however: for some jobseekers the information treatment encourages faster job finding, while for others, it discourages job search altogether and shifts them from unemployment into passive support schemes.

Keywords: Job search, long-term unemployment, information provision, statistical profiling, regression discontinuity

JEL codes: J68, D83, C93

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1 Introduction

Recent evidence shows that unemployed workers often overestimate their reemployment prospects (Mueller et al., 2021; Mueller and Spinnewijn, 2023; Spinnewijn, 2015). Since these misperceptions can distort job search behavior and prolong unemployment, a natural policy response is to implement information provision strategies designed to correct these beliefs. However, it is theoretically unclear whether such policies will actually improve employment outcomes. When jobseekers learn that job finding may be harder than expected, this could encourage them to intensify their job search, thereby improving reemployment prospects. Alternatively, it could discourage them and lead them to give up on finding a job altogether.

In this paper, we study the causal effects of a large-scale information provision policy targeting unemployment insurance (UI) recipients in the Danish labor market. Aligning with international evidence, Danish UI recipients tend to overestimate their reemployment prospects. Against this backdrop, between 2015 and 2017, approximately 40% of new UI recipients were assessed using a statistical profiling tool that predicted their risk of long-term unemployment based on various characteristics. Subsequently, those with a high predicted risk received a message about their negative reemployment outlook. The policy aimed to correct these individuals' overly optimistic beliefs, encouraging them to adjust their job search behavior and leave unemployment faster.

We analyze the effect of this information treatment on the likelihood of exiting unemployment. To establish causality, we leverage that the underlying profiling tool lends itself to a regression discontinuity (RD) design using jobseekers' age as the running variable. The profiling tool builds on a decision tree that includes age as a key splitting variable. This means that many jobseekers receive the information treatment based on their exact age at the time of profiling, with cutoffs at ages 28, 29, 54, and 56. By comparing individuals just above and below these age cutoffs, we obtain quasi-random variation in treatment assignment.

In line with the policy's objective, the information treatment promotes exits from unemployment: after six month, jobseekers who are just above the relevant age cutoff and receive the information treatment are seven percentage points less likely to receive unemployment benefits compared to those just below the cutoff. However, this effect could either indicate that jobseekers are encouraged to find employment faster or that they become discouraged, abandon their search, and leave UI without securing paid employment. To distinguish between such encouragement and discouragement effects, we analyze the impact of the information treatment on the likelihood of exiting unemployment into paid employment, as well as into passive support programs – such as sickness or parental benefits – that provide income support without requiring active job search. Given the significant differences in the relevance of various passive support programs across socio-demographic groups, we conduct this analysis separately by gender and by age, distinguishing between treatment cutoffs at ages 28-29 and 54-56.

The effect of the information treatment differs markedly across these demographic groups, indicating the presence of both encouragement and discouragement effects. We observe the strongest evidence of encouragement effects among young men. For this group, the information treatment leads to a significant increase in unemployment exits, mainly driven by transitions into paid employment. Additionally, the information treatment encourages some young men to leave unemployment to pursue further education and receive education benefits. Young women, on the other hand, appear to be discouraged from actively seeking employment. For them, the information treatment results in an increased uptake of parental benefits and a higher likelihood of leaving unemployment without securing employment or receiving other benefits. Among older jobseekers, we find that women tend to exit unemployment primarily due to an increase in paid employment when informed about their heightened risk of long-term unemployment. Conversely, we find evidence of discouragement effects for older men, where the information treatment leads to an increased uptake of sickness benefits.

We interpret our empirical findings through the lens of a simple job search framework: jobseekers decide on their search effort while also having the choice to exit unemployment without finding a job, relying instead on passive support or personal savings. The information treatment causes jobseekers to lower their expectations about their reemployment prospects, leading to heterogeneous behavioral responses. Under appropriate functional form assumptions, the revised beliefs encourage some workers to intensify their search efforts, promoting job finding and exits from unemployment. This is consistent with our findings for young men and older women. At the same time, the diminished reemployment prospects decrease the continuation value of receiving unemployment benefits and actively seeking employment. When passive support is relatively appealing, this may discourage job search entirely, leading to exits from unemployment into passive support instead. This aligns with our findings for young women, who may prefer additional childcare time, and possibly with the results for older men who opt for sickness benefits after leaving unemployment.

Our study relates to the growing body of research demonstrating that jobseekers tend to be overly optimistic about their labor market prospects, including job finding (Balleer et al., 2021; Mueller et al., 2021; Mueller and Spinnewijn, 2023; Spinnewijn, 2015) and their earnings potential (Caliendo et al., 2023; Conlon et al., 2018; Krueger and Mueller, 2016). A key contribution of our study is that we estimate the causal effects of an actual large-scale information provision policy that aims to correct these beliefs.

Additionally, our study contributes to the literature on the use of profiling tools in the labor market. Similar to our setting, these tools use individuals' characteristics as input for statistical models to identify common patterns, including predicting long-term unemployment risk. In most other settings, however, this information is used to assign specific treatments, such as active labor market policies (see, e.g., Behncke et al., 2009; Black et al., 2007; Frölich, 2008; Lechner and Smith, 2007; Staghøj et al., 2010), without sharing the outcomes of the profiling process with the individual. Our results also provide new insights to the literature on online labor market interventions designed to address the specific needs of individual jobseekers (see e.g. Altmann et al., 2022; Behaghel et al., 2022; Belot et al., 2019, 2022; Ben Dhia et al., 2022; Horton, 2017).

2 Empirical Setup

2.1 Unemployment and social security in Denmark

In Denmark, unemployment benefits are organized in a voluntary opt-in system. Eligible jobseekers can receive benefit payments for a maximum of two years if they have made contributions for at least 12 months within the past three years. The replacement rate is set at 90% of prior wage income, capped at DKK18,866 (USD3,075) per month before taxes. To remain eligible for benefits, recipients must actively search for jobs and document their search activities.

Depending on their circumstances, unemployed individuals may also be eligible for other forms of public support. Individuals can qualify for educational benefits if they enroll in a secondary or tertiary education program or vocational training. Moreover, individuals can present a medical certificate to receive sickness benefits instead of unemployment benefits for up to 22 weeks. Finally, there exists a flexible parental leave system that allows parents, including those who are unemployed, to be involved in childcare. While mothers are entitled to maternity leave for 14 weeks immediately after childbirth, either parent can take additional parental leave for up to 32 weeks. In general, the level of sickness or parental benefits is the same as the level of unemployment benefits. Importantly, however, individuals on any of these forms of passive support no longer face job search requirements.

2.2 Profiling tool and information treatment

When becoming unemployed, all jobseekers in Denmark register at the online portal of the Danish Employment Agency (*jobnet.dk*) to receive unemployment benefits. Upon registration, they are asked to answer a voluntary online survey.[1] The survey is advertised as preparation for their first caseworker meeting and covers 12 questions related to their education, job search strategies, job preferences, and reemployment expectations. About 40% of all newly unemployed individuals answer the survey, and more than 80% of respondents answer during the first two weeks of unemployment.

During our study period (July 2015 - August 2017), the survey responses of participants who completed the questionnaire were combined with additional administrative data and fed into a statistical profiling tool.[2] As explained in more detail below, the profiling tool generates a prediction indicating whether individuals face a heightened risk of long-term unemployment, defined as being unemployed for 26 weeks (six months) or longer. Moreover, upon completing the survey, jobseekers receive an immediate feedback message. For all respondents, the survey concludes with an on-screen message expressing gratitude for their participation and explaining how their survey responses will be valuable for their upcoming caseworker meeting. For individuals classified as 'high risk', however, the screen includes an additional paragraph that informs them about their heightened risk of long-term unemployment:

> *Your characteristics indicate that reentering employment might be challenging for you. Our analysis reveals that persons with similar characteristics, who were previously unemployed like you, encountered greater difficulties in securing new employment compared to other unemployment benefit recipients. We recommend discussing and planning the necessary steps with your caseworker to find a job quickly.*

The aim of the message is to make jobseekers aware of their higher likelihood of long-term unemployment. As we return to in Section 3, we expect that this will lead the typical jobseeker to downward revise their optimistic beliefs about reemployment prospects.

We note that – in addition to conveying this message to the jobseeker – the categorization of the individual as either high risk or not is also shared with the caseworker who is responsible for assisting the jobseeker during the search process. In principle, the profiling tool and information treatment could thus potentially influence employment outcomes by altering caseworkers' behavior. In practice, this does not seem to be the case, as the majority of caseworkers report that their counseling of jobseekers is not influenced by the risk assessment from the statistical model (STAR, 2021). Moreover, as we discuss in Section 4.3, our empirical findings also indicate no evidence that caseworkers respond to the information treatment.

[1]For all individuals who had not received benefits within the last 180 days, the survey is available for twelve weeks after registration.

[2]We analyze the first profiling tool that was in use from July 2015 to August 2017 (STAR, 2015). Afterwards, the statistical model was revised, and the risk assessment was abolished in March 2022.

2.3 Discontinuities in the profiling tool

The profiling tool was developed by the Danish Employment Agency and is based on a simple machine-learning algorithm, trained to predict long-term unemployment. The algorithm relies on a single decision tree that examines a range of observable characteristics – including age, ethnicity, previous (un)employment, former industry, education, and past receipt of public benefits. The decision tree determines whether an individual is at high risk of long-term unemployment by sequentially checking the value of the different variables used in the algorithm. High-risk individuals in turn receive the information treatment message.

For our empirical analysis, we leverage the fact that the decision tree creates age discontinuities in treatment assignment. Conditional on jobseekers' other characteristics, whether they receive the information treatment in many cases depends on whether their age has surpassed a specific cutoff.[3] For example, a jobseeker with no employment in the previous year and an educational background in health is identified as 'high risk' and receives the information treatment only if she is over 29 years old at the time of profiling. As another example, a jobseeker who was employed in the previous year, has experience in public administration, and has not received UI benefits in the past five years will receive the information treatment only if she is over 56 years old. Our analysis leverages such age discontinuities in treatment assignment to establish a regression discontinuity (RD) design.

2.4 Data and regression discontinuity design

Our raw data contains all newly registered UI recipients between July 2015 and August 2017 who answered the online survey discussed in Section 2.2. We directly observe their survey responses and the outcome of the profiling process – whether they are classified as high risk and receive the information treatment message. Moreover, we link the survey information to administrative data to reconstruct all input variables used in the profiling model and to observe individuals' realized labor market outcomes.

With this data, we apply the decision tree to all worker input variables, *excluding* age. This partitions the sample into 27 different subgroups (nodes in the decision tree) based on their non-age characteristics (see Online Appendix Figure A.1). In eight of these subgroups, age does not affect treatment assignment, so they cannot be used in our RD design. In the remaining 19 subgroups, treatment assignment depends on whether the worker's age crosses a

[3] Online Appendix Figure A.1 shows a full representation of the actual decision tree underlying the profiling tool in which age is always the last variable examined along all branches whenever possible. Note that a given decision tree does not have a unique graphical representation as the order of the splitting variables can be altered. As we progress through our representation of the tree, we either end up at a terminal node without considering individual's age (see blue nodes) or we examine individuals' age against one or more cutoffs before reaching a terminal node (see red nodes).

particular threshold. Upon inspection, 12 of these groups have only very few individuals near the age threshold, so we exclude them from our analysis. Additionally, we exclude one subgroup consisting entirely of individuals of non-Danish origin. These individuals typically face distinct labor market challenges and potential language barriers may limit the impact of the information treatment.

After imposing these restrictions, we are left with six sizable subgroups (nodes) where treatment assignment is determined by an age cutoff. These form our main analysis sample. Depending on the subgroup, the age cutoffs determining treatment are either 28, 29, 54, or 56 years. We note that focusing on observations around these cutoffs will always result in a sample with a distinctly bimodal age distribution. We return to this in Section 4.2.

To set up our RD specification, we construct the running variable, RV_i, for each person i as the difference between their age at the time of completing the survey and the relevant age cutoff (28, 29, 54 or 56). In the absence of measurement error, we would *predict* all individuals where $RV_i \geq 0$ to receive the information treatment and all individuals with $RV_i < 0$ to not be treated. For some individuals, however, the predicted treatment will deviate from *received* treatment due to idiosyncratic measurement error in the historical input variables used in the profiling tool. Due to updates in the employment agency's administrative data, the input variables we construct ex post may sometimes differ slightly from those used when applying the profiling tool in real time.[4] This will lead us to assign some jobseekers to the wrong subgroup and cutoff.

The existence of such measurement error effectively implies that our RD design is fuzzy. Since the measurement error is in fact negligible, we focus our main results on intention-to-treat effects (ITTs) of the information treatment on labor market outcomes.[5] We obtain these by estimating the following equation on the (weighted) sample of individuals with RV_i close to zero:

$$Y_i = \beta_0 + \beta_1 RV_i + \beta_2 RV_i \times T_i + \tau T_i + \beta_3 X_i + \varepsilon_i, \tag{1}$$

RV_i is the running variable (measured in weeks) determining treatment and T_i is an indicator for crossing the treatment threshold ($RV_i \geq 0$). X_i corresponds to a set of predetermined control variables. Besides examining average effects of the information treatment on the overall sample, we conduct separate analyses for distinct groups of jobseekers – based on gender and age –

[4]Input variables, such as the 'share of the past year spent on UI,' may undergo minor revisions as additional reports are received from various agencies. When assigning workers to subgroups, which determines their treatment status based on potential age cutoffs, we use the most recent available data. If this differs significantly from the data at the time of survey completion, we may assign the worker to the incorrect age cutoff.

[5]We present 2SLS estimates of the Local Average Treatment Effect in Table A.3 of the Online Appendix. However, since the estimated first stage coefficient exceeds 0.85, these estimates are very close to the estimated ITT.

who are expected to exhibit heterogeneous responses to the information treatment (see also Section 3).

In our main specification, we include observations within the optimal bandwidth that minimizes the mean squared error (Cattaneo et al., 2017) for our main outcome variable: an indicator of whether an individual continues to receive unemployment benefits 26 weeks after survey completion, which corresponds to the outcome of the profiling model. Moreover, we weight observations using a triangular kernel and control for a rich set of predetermined jobseeker characteristics. We exclude individuals who complete the survey in week zero (the week corresponding to their actual crossing of the threshold) due to the potentially heightened measurement error for such instances. Additionally, we examine the robustness of our findings by conducting inference using robust confidence intervals (see Calonico et al., 2014; Cattaneo et al., 2019), and using a quadratic specification instead of a linear one.

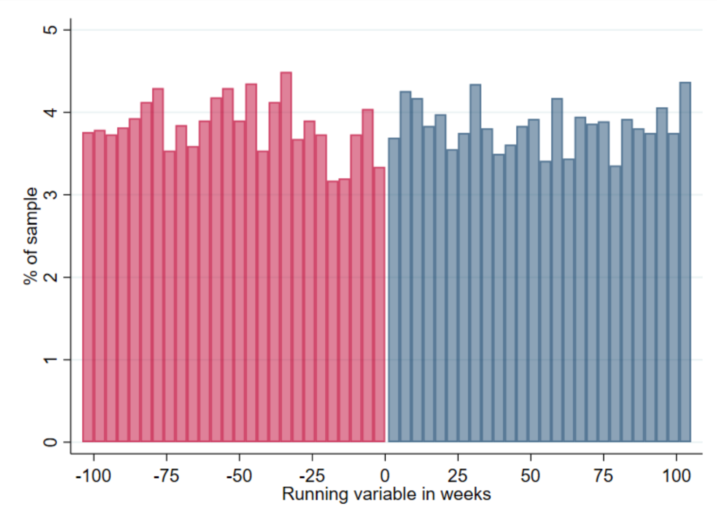
2.5 Validity of empirical approach

To ensure that the RD approach accurately identifies the causal effect of the information treatment, it is critical that individuals on both sides of the cutoff are similar in all relevant characteristics except for their treatment assignment (i.e. no systematic sorting). We argue that this assumption is highly plausible in our context: there are no incentives or institutional features that would encourage individuals to enter UI or complete the survey just before or after reaching a specific age threshold. Importantly, the survey invitation received by newly unemployed individuals does not mention the profiling tool, and the existence of the tool – let alone the specific algorithm used – is not common knowledge.

To provide empirical support for the identifying assumption, Figure 1 shows the continuity of the density function for the running variable around the cutoff (see McCrary, 2008). We observe only minor distributional differences below and above the cutoff, and a statistical test does not reject the null hypothesis that the density of the running variable is continuous around the cutoff ($p = 0.178$).

In Online Appendix Table A.2 we further examine whether there exist discontinuities in predetermined characteristics – including socio-demographics and labor market histories. We see no indications of this – across more than 30 balancing tests, only two turn out to be statistically significant at the 10%-level. This supports the notion that individuals just above and below the cutoff are indeed comparable to each other.

Figure 1: Distribution of running variable



Note: The figure shows the distribution of the running variable (measured in weeks) around the age cutoff defining whether individuals are predicted to be at low or high risk of long-term unemployment.

2.6 Baseline beliefs and predictive power of information treatment

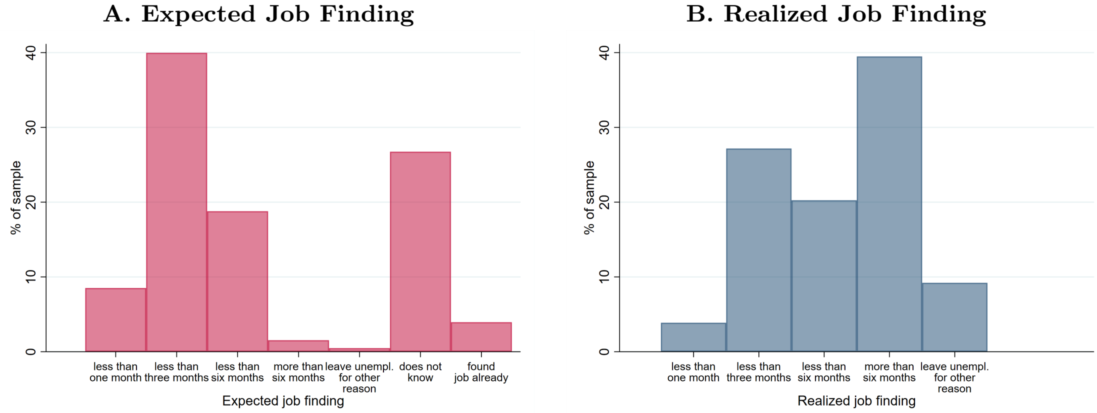
Before examining the effects of the information treatment, we present descriptive evidence on jobseekers' beliefs about their reemployment prospects. In addition to the questions used for the profiling tool, the survey that new UI recipients receive also asks about their expected speed of job finding. Using the group of non-treated individuals within a bandwidth of 150 weeks below the cutoff, we can compare these beliefs with their realized outcomes to examine baseline beliefs in the absence of the information treatment.

In line with previous evidence, Figure 2 suggests that unemployed workers in Denmark are overoptimistic about their reemployment prospects. Approximately 48.5% of jobseekers expect to find a job within three months, whereas only 31% actually do so. Similarly, only 2% of the workers in our sample anticipate job finding to require more than six months but the reality is that 40% have still not secured a job after six months.

Given these overly optimistic baseline beliefs, we expect the information treatment to correct beliefs downward among treated individuals. This, of course, assumes that jobseekers view the provided information as both trustworthy and new. In Appendix Table A.7, we substantiate this by showing that the information from the profiling tool is predictive of actual unemployment durations, both unconditionally and after accounting for individuals' reported baseline beliefs.[6] At least under a Bayesian learner benchmark, this implies that jobseekers *should* revise their beliefs downward in response to the information.

[6] Appendix Table A.7 shows that during the pre-profiling period from April 2014 to June 2015 – when no one received the information treatment – individuals identified as 'high risk' by the profiling tool were more likely to remain unemployed after six months, even after controlling for their reported baseline beliefs.

Figure 2: Baseline Beliefs and Realized Job Finding



Note: The figure shows the distribution of the perceived and realized job finding prospects among non-treated individuals within a bandwidth of 150 weeks below the age cutoff ($N = 5,189$).
The expected job-finding prospects (Panel A) is elicited during the survey before treated jobseekers were informed about their heightened risk of long-term unemployment using the following question: *How quickly do you think you will find a new job?*
The corresponding realized job finding (Panel B) refers to the duration between the completion of the survey and the first month in which the individual was employed (as observed in the administrative records). The category 'leave unempl. for other reason' accounts for all jobseekers taking up an education, sickness or parental benefits.

3 Theoretical Framework

The descriptive evidence suggests substantial scope for individuals to adjust their subjective beliefs and that it is reasonable for the average treated jobseeker to raise their perceived risk of long-term unemployment. In this section, we theoretically illustrate how updating jobseekers' beliefs may influence their behavior.

3.1 Job search framework

While receiving unemployment benefits, individuals search for jobs and receive a flow utility of b. Individuals choose their level of search effort, s, which affects the rate at which job offers arrive, according to the arrival rate $\lambda(s)$. Inspired by Mueller and Spinnewijn (2023), jobseekers hold subjective beliefs about the job arrival rate, $\widehat{\lambda}(s)$, and maximize utility as if $\widehat{\lambda}(s)$ represents the true function. We assume that $\widehat{\lambda}(s)$ is an increasing and concave function. For illustrative purposes, we further assume that all jobs offer the same wage, denoted by V, and that this value is high enough to be preferred over unemployment.[7] Effort costs incurred during job search are captured by the increasing and convex function $\gamma(s)$.

We denote the value of unemployment while exerting search effort s and facing a specific (perceived) job offer arrival rate of λ as $U(s, \lambda)$. Assuming a time discount rate of ρ, this satisfies

[7] This assumption means that we abstract from individuals' reservation wage choice, the minimal job offer they would accept. If jobs offer varying wages and jobseekers sometimes reject offers, they may lower their reservation wage upon learning about the diminished perceived returns to search. This, in turn, may reinforce faster job finding and exit from unemployment.

a standard asset pricing equation reflecting the flow benefits and costs, and the likelihood of transitioning to employment:

$$\rho U(s,\lambda) = b - \gamma(s) + \lambda\left(V - U(s,\lambda)\right) \tag{2}$$

Moreover, we allow for the possibility that jobseekers may exit unemployment for various forms of passive support, with the most attractive option offering an exogenously fixed continuation value of R. Depending on the individual, this could involve starting a new education and receiving educational support, receiving sickness or parental benefits, or even some form of self-support without a job.

In this framework, individuals' optimal decisions have a simple, useful characterization. First, while receiving unemployment benefits and actively seeking employment, we can think of a jobseeker as jointly selecting a combination of search effort, s, and the corresponding job finding rate based on their subjective beliefs, $\widehat{\lambda}(s)$. We let $\bar{U}$ denote the value of being unemployed when making this choice optimally:

$$\bar{U} = \max_{s,\lambda} U(s,\lambda) \quad \text{s.t.} \quad \lambda = \widehat{\lambda}(s) \tag{3}$$

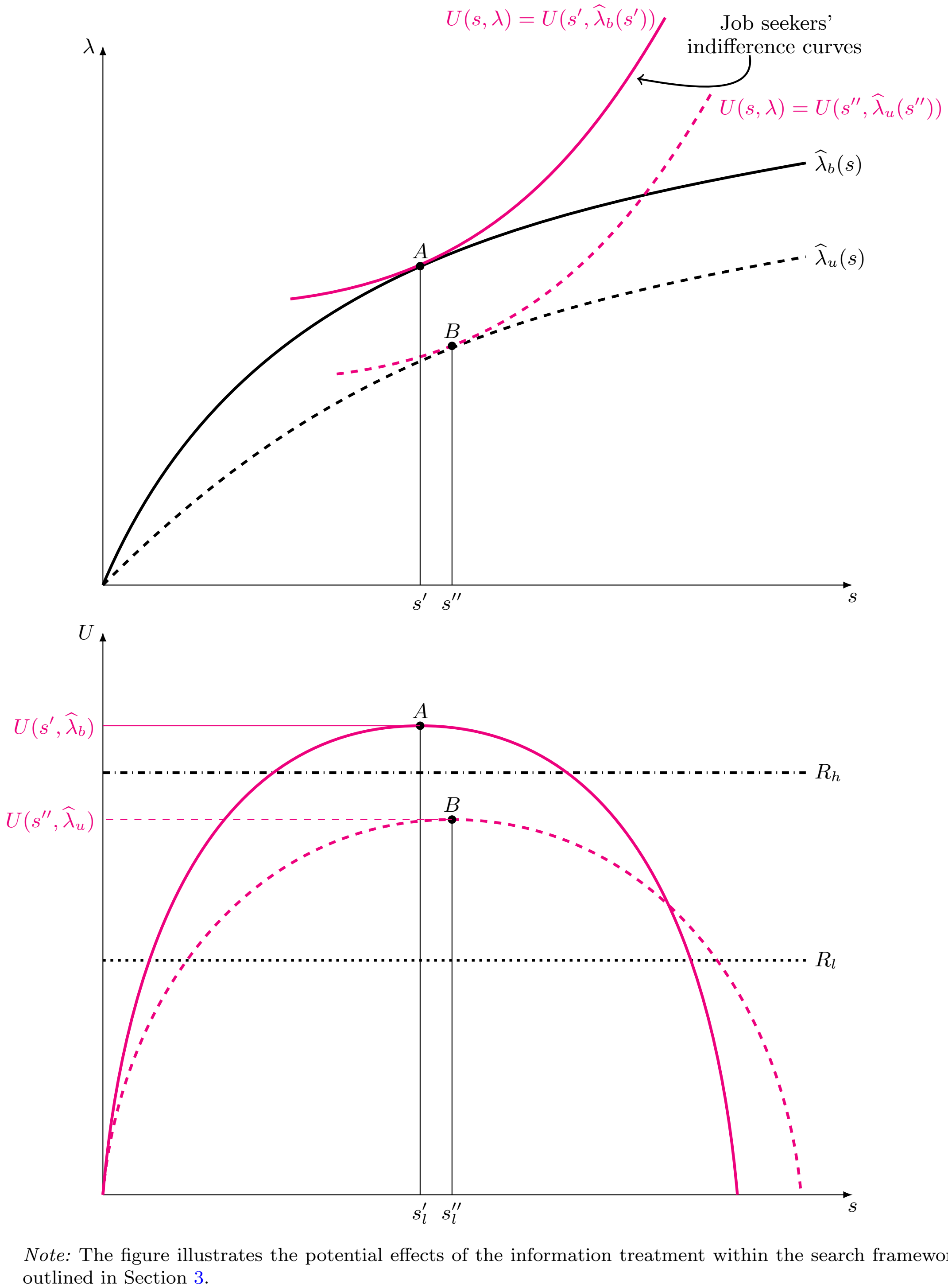
The solution to this maximization problem defines the optimal search effort, s^*, when receiving unemployment benefits. Moreover, the decision of whether to remain on unemployment benefits or opt for passive support is straightforward, and based on comparing the continuation values. The overall continuation value W is given by $W = \max\left\{R, \bar{U}\right\}$. If $\bar{U} \geq R$, it is optimal to receive unemployment benefits and continue searching. Otherwise, the individual will choose to exit into passive support.

3.2 Potential effects of the information treatment

The information treatment informs treated jobseekers that they have a heightened risk of long-term unemployment. As noted, we expect this to *lower* their expectations regarding the likelihood of success when searching for employment. We therefore consider the comparative statics of transitioning from some initial perceived job offer arrival rate $\widehat{\lambda}_b(s)$ to a less optimistic one, denoted as $\widehat{\lambda}_u(s)$, where $\widehat{\lambda}_u(s) \leq \widehat{\lambda}_b(s)$.

We first examine the effect of this change on optimal search effort, conditional on remaining on unemployment benefits. As emphasized by Mueller and Spinnewijn (2023), this effect is ambiguous and depends on the precise difference in the shape of $\widehat{\lambda}_b(s)$ and $\widehat{\lambda}_u(s)$. Under suitable functional form restrictions, however, the revised beliefs will lead to increased search effort, as workers come to realize that they need to search harder to successfully find a job. ("encourage-

Figure 3: Graphical Illustration of Potential Treatment Effects



Note: The figure illustrates the potential effects of the information treatment within the search framework outlined in Section 3.

The upper panel illustrates how the information treatment potentially encourages job seekers to increase their search effort, s. The treatment reduces the perceived job finding rate from $\widehat{\lambda}_b(s)$ (black solid line) to $\widehat{\lambda}_u(s)$ (black dashed line). For the job seeker characterized by the red indifference curves, this induces an increase in the optimal effort level from s' to s''. The overall value of being on UI is reduced from $U(s,\lambda) = U(s', \widehat{\lambda}_b(s'))$ to $U(s,\lambda) = U(s'', \widehat{\lambda}_u(s''))$. In addition to the illustration above, Figure A.2 in the Online Appendix depicts a scenario where the information treatment leads to a reduction in the optimal effort.

The lower panel depicts the relationship between job seekers' search effort, s, and the perceived value of search, U, before (red solid line) and after (red dashed line) receiving the information treatment. The perceived value of search decreases from $U(s', \widehat{\lambda}_b)$ to $\rho U(s'', \widehat{\lambda}_u)$ due to the information treatment. Given that $U(s'', \widehat{\lambda}_u) < R_h$, individuals eligible for the high outside option, R_h (represented by the dash-dotted line), cease their search activities entirely. Given that $U(s'', \widehat{\lambda}_u) > R_l$, individuals eligible for the low outside option, R_l (dotted line) continue their search and adjust their search effort as illustrated in the upper panel.

ment effect"). As will be clear from our results, this seems to be the empirically relevant case in our setting and the upper panel of Figure 3 illustrates such a scenario.[8]

The initial maximization problem (see Equation (3)) can be visualized as selecting a combination of s and λ along the curve $\widehat{\lambda}_b(s)$, where utility increases as one moves upwards and to the left. When beliefs change, the curve shifts downwards to $\widehat{\lambda}_u(s)$, resulting in a new optimum with higher search effort.

Since the change in beliefs also reduces the perceived value of unemployment, however, it may also influence the decision to continue receiving unemployment benefits versus switching to passive support. We illustrate this in the lower panel of Figure 3. The change in beliefs reduces the value of unemployment, $\bar{U}$. As a result, jobseekers who have access to relatively attractive passive support, R_h, may find it preferable to give up their job search and switch to passive support. Conversely, jobseekers with only less attractive passive support options, R_l, are likely to remain on unemployment benefits and continue their search at a higher effort level.

In summary, this simple framework suggests that the information treatment may encourage exits from unemployment. However, these exits could result from either faster job finding or from job seekers becoming discouraged and transitioning to passive support schemes.

4 Results

4.1 The effect of the information treatment on exits from unemployment

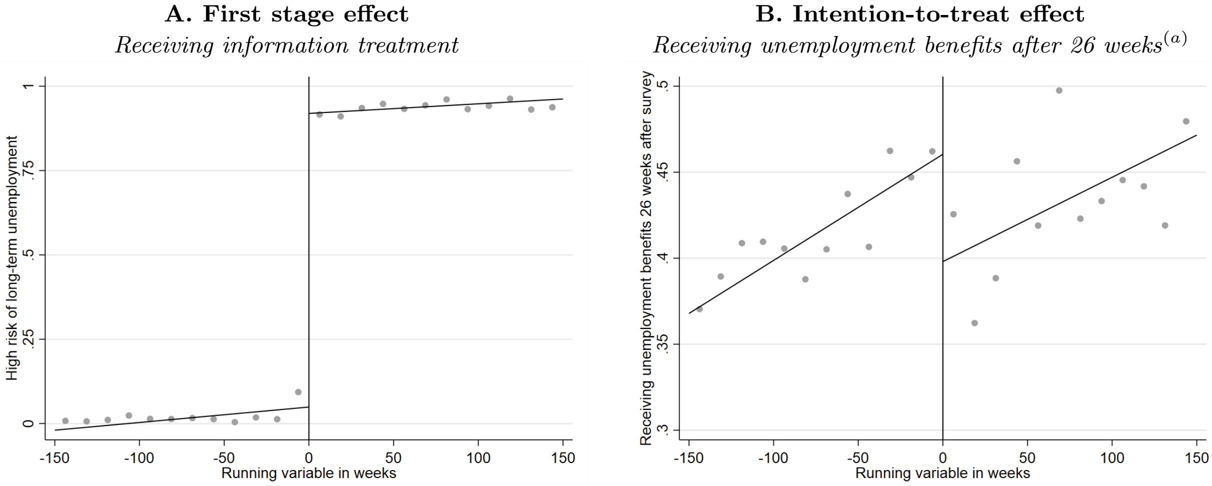
We start our RD analysis by examining whether receiving the information treatment leads jobseekers to exit unemployment faster overall. Given the objective of the information treatment, we focus on the likelihood of receiving unemployment benefits 26 weeks after survey completion.

Figure 4 shows graphical RD results. Panel A shows the share of individuals receiving the information treatment in relation to the value of the running variable. As anticipated, crossing the treatment threshold causes a discontinuous jump in the likelihood of receiving the information treatment, rising from near zero to about 90 percent. As discussed earlier, the slight imperfect compliance is due to minor measurement errors in the profiling tool's input variables.

Panel B illustrates the intention-to-treat (ITT) effect by plotting the share of individuals who receive unemployment benefits after 26 weeks against the running variable. Again, there is a clear discontinuous change at the treatment threshold. Treated individuals just above the cutoff are approximately seven percentage points less likely to remain unemployed after 26 weeks compared to those just below the cutoff. Corresponding numerical ITT estimates are available in Appendix Table A.3. In comparison to the sample average, our estimates indicate that the treatment

[8]The opposite case would imply that downwards correcting beliefs leads to a reduction of search effort. We graphically illustrate such an 'intensive margin discouragement' scenario in Appendix Figure A.2.

Figure 4: Graphical illustration of regression discontinuity



Note: The figure illustrates the regression discontinuity around the age cutoff. Panel A depicts the relationship between the running variable and the likelihood of actually receiving the information treatment after survey completion. Panel B depicts the relationship between the running variable and the likelihood of still receiving unemployment benefits 26 weeks later. Each dot represents the average for individuals within bins of the running variable, while the solid lines represent an RD-regression fitted to the underlying data.
[a]Includes public benefits subject to job search requirements, for example unemployment insurance (UI) benefits and social assistance.

significantly reduces the probability of becoming long-term unemployed by 6.8 percentage points or about 16% ($p = 0.004$). This result is robust to alternative specifications, including dropping control variables, using a quadratic instead of a linear specification and switching from a data-driven optimal bandwidth to a more restrictive manual choice.

4.2 Exits to employment vs. other support programs

The results above confirm that the information treatment leads to faster unemployment exit, in line with both the policy's overall objective and with the predictions of the theoretical framework from Section 3. However, the additional exits from unemployment could reflect both encouragement effects, where jobseekers increase search effort, and discouragement effects, where jobseekers abandon job search entirely and transition into passive support. To disentangle these effects, we next decompose the effect of the information treatment on the uptake of various types of public benefits and employment.

To conduct a meaningful analysis of transitions into other support programs, we need to split the data into subgroups due to the composition of our RD sample. As noted in Section 2.4, our sample effectively contains two age groups: young workers in their late twenties (around age cutoffs 28 and 29) and older workers in their mid-fifties (around age cutoffs 54 and 56). We analyze these groups separately to account for their differential incentives and possibilities regarding passive support. In terms of lifetime income, leaving the labor force near pension age has very different effects compared to doing so early in one's career. Moreover, passive support programs such as educational support and parental leave are primarily relevant for younger workers. Finally, due to the pronounced gender disparity in parental leave uptake, we also conduct our analyses separately by gender.

Panel A of Table 1 presents RD estimates of the effect of the information treatment on the likelihood of receiving various forms of support or no public benefits after 26 weeks. Additionally, we decompose the outcome receiving 'no public benefits' into paid employment and self-support through other means. First, we re-estimate the effect of the information treatment on the likelihood of receiving unemployment benefits after 26 weeks, with separate analyses for each worker subgroup. For all four subgroups, the estimated effect on the likelihood of receiving unemployment benefits is negative, although the magnitude and precision of the coefficients vary. The effect is estimated to be most pronounced for young men (-29.7pp, $p = 0.002$), while the effect for older men is markedly smaller and not statistically significant (-1.9pp, $p = 0.643$). The estimated effect for both young and older women is similar to the overall effect (-4.6pp and -8.9pp, respectively). However, only the effect for older women is statistically significant ($p = 0.022$), while the effect for young women is not ($p = 0.534$).[9]

Despite the broadly similar effects on exits from unemployment, we see very pronounced differences across the four subgroups when considering the likelihood of receiving other forms of public benefits after 26 weeks. For young men, the information treatment notably increases the likelihood of receiving education benefits (+6.8pp; $p = 0.029$) and exiting public benefits entirely (+22.3pp; $p = 0.021$). The latter seems to primarily reflect increased job finding, although the estimated effect on paid employment is not statistically significant at conventional levels (+14.2pp; $p = 0.137$). For young women, the information treatment increases the likelihood of being on parental leave (+5.9pp; $p = 0.022$) and the likelihood of leaving unemployment benefits without securing paid employment or receiving other benefits (+9.5pp; $p = 0.039$).[10]

Viewed through the lens of the theoretical framework from Section 3, these results are consistent with the notion that young men primarily experience an encouragement effect, while young women encounter a discouragement effect. After receiving the information treatment, most young men are motivated to search harder because they lack attractive alternatives. In contrast, for many young women, additional childcare time on parental leave or time out of the labor force may present a relatively appealing alternative. The discouragement induced by the information treatment leads them to abandon their job search altogether, at least temporarily.

[9] Pairwise tests of the estimated effects reveal that the effect for young men is significantly different from those for the other groups. However, we cannot reject the hypothesis that the effects are the same for the remaining three groups.

[10] Notably, the vast majority (93%) of women receiving parental benefits 26 weeks post-treatment are expecting a child at the time of the survey, with few using leave for earlier-born children.

Table 1: Heterogeneous Effects of Information Treatment on Benefit Take-Up

	Men – young (1)	Women – young (2)	Men – old (3)	Women – old (4)
Panel A: Benefit take-up 26 weeks after survey completion				
Unemployment benefits[(a)]	-0.297***	-0.046	-0.019	-0.089**
	(0.095)	(0.074)	(0.041)	(0.039)
Educational support	0.068**	-0.024	-0.001	0.001
	(0.031)	(0.031)	(0.003)	(0.006)
Sickness benefits	-0.000	0.009	0.035*	0.021
	(0.024)	(0.033)	(0.018)	(0.020)
Parental leave	0.006	0.059**	0.000	0.000
	(0.007)	(0.024)	(0.000)	(.)
No public benefits[(b)]	0.223**	0.001	-0.016	0.067*
	(0.096)	(0.073)	(0.041)	(0.038)
hereof paid employment[(c)]	0.142	-0.094	-0.055	0.053
	(0.095)	(0.065)	(0.040)	(0.038)
hereof other self-support[(d)]	0.081	0.095**	0.045*	0.015
	(0.070)	(0.046)	(0.026)	(0.022)
Panel B: Benefit take-up 52 weeks after survey completion				
Unemployment benefits[(a)]	-0.179**	0.046	-0.024	-0.021
	(0.086)	(0.063)	(0.038)	(0.035)
Educational support	0.041	-0.037	0.002	-0.004
	(0.042)	(0.033)	(0.003)	(0.007)
Sickness benefits	-0.074	-0.047	0.002	-0.014
	(0.046)	(0.042)	(0.017)	(0.021)
Parental leave	-0.001	0.100***	0.000	0.000
	(0.006)	(0.037)	(.)	(.)
No public benefits[(b)]	0.212**	-0.062	0.025	0.040
	(0.101)	(0.072)	(0.040)	(0.037)
hereof paid employment[(c)]	0.149	-0.052	-0.007	-0.002
	(0.102)	(0.073)	(0.041)	(0.037)
hereof other self-support[(d)]	0.064	-0.030	0.031	0.039*
	(0.079)	(0.046)	(0.024)	(0.022)
No. of observation	454	823	3,629	3,557
Bandwidth in weeks	[-70:120]	[-87:121]	[-224:91]	[-138:78]

Note: The table reports intention-to-treat effects of the information treatment based on RD regressions for various subgroups. The young sample includes men and women facing age cutoffs in their late twenties (age 28 or 29). The old sample includes men and women facing age cutoffs in their mid-fifties (age 54 or 56). We include observations within the "optimal bandwidth" around the age cutoff and weight observations using a triangular kernel. The "optimal bandwidth" is subgroup specific, and obtained based on the outcome variable "receiving unemployment benefits 26 weeks after survey completion". Appendix Table A.4 shows the results are robust to using a sub-group and outcome specific "optimal bandwidth". In all specifications, we include controls for predetermined individual characteristics, including number of children, marital status, level of education, average monthly working hours and earnings in the year prior to job loss, and previous industry. For the young sub-groups (men and women), we additionally control for whether the individual is expecting a child at the time of the survey. Standard errors are reported in parentheses. ***/**/* indicates statistical significance at the 1%/5%/10%-level, respectively.

[(a)]The measure is equal to one if the individual receives public benefits subject to job search requirements, that is, unemployment insurance (UI) benefits or social assistance.

[(b)]The measure is equal to one if the individual does not receive any public benefit payments in the corresponding week. This includes paid employment, self-employed, being out of the labor force or having move abroad.

[(c)]The measure is equal to one if the individual is paid employed (only observed at the monthly level) and does not receive public benefits in the corresponding month.

[(d)]The measure is equal to one if the individual is not paid and and does not receive public benefits in the corresponding month.

Examining the samples of older men and women reveals stark gender differences and evidence of both encouragement and discouragement effects. However, the gender patterns are reversed in this case. The information treatment makes older women significantly less likely to receive public benefits (-6.7pp; $p = 0.079$), which primarily appears to reflect an encouragement effect, as they are motivated to find paid employment (+5.3pp; $p = 0.163$). For older men, however, the treatment appears to discourage active job search, increasing the likelihood of going on sickness benefits (+3.5pp; $p = 0.052$) or exiting unemployment without securing employment (+4.5pp; $p = 0.079$).[11]

Finally, in Panel B of Table 1, we assess the persistence of the estimated effects by repeating the analysis for outcomes after one year (52 weeks) instead of six months (26 weeks). The results show a similar pattern, suggesting that the treatment effects are persistent.

4.3 Additional results

We complement our analysis by providing empirical evidence on three additional aspects.

Reservation wages and hours? In our theoretical framework, we assumed that all jobs were identical, meaning that higher job finding rates could only result from increases in search effort. In practice, however, the estimated effects could also reflect reductions in reservation wages or hours if the information treatment makes workers less selective. Panel A of Appendix Table A.5 examines treatment effects on accumulated working hours and labor earnings. Overall, the estimated effects align with the intensive margin effects documented in Table 1, though the precision is insufficient to draw further conclusions about the underlying mechanisms.

Workers' beliefs or caseworkers' responses? The outcome of the profiling tool, categorizing individuals as being at risk or not, is not only shared with the jobseeker, but also with their caseworker. Hence, a possible explanation for the observed effects could be that caseworkers adjust their behavior in response to the information(see, e.g., Behncke et al., 2010; Schiprowski, 2020). To test this, Panel B of Appendix Table A.5 examines treatment effects on key outcomes controlled by the caseworker, namely the frequency of caseworker meetings and the likelihood of being assigned to an active labor market program (see, e.g., Humlum et al., 2023). We see no evidence that caseworkers respond to the profiling tool information. This aligns with evidence from caseworker interviews, indicating that most caseworkers do not rely on the risk assessment from the profiling tool (STAR, 2021).

[11] One possible explanation for the gender differences among older workers is the disparity in accumulated pension savings. It is well established that men tend to have accumulated more pension savings than women by the end of their careers, making it relatively more attractive for men to opt for passive support in the years leading up to retirement.

Heterogeneity by baseline confidence: Jobseekers may respond differently to the information treatment depending on their prior beliefs. Therefore, Appendix Tables A.6 and A.7 examine heterogeneity based on individuals' baseline confidence about their reemployment prospects. The results in Table A.6 suggest that the positive treatment effects on job finding are more pronounced (and statistically significant) for jobseekers with moderate levels of baseline confidence compared to those who are most confident. However, as shown in Table A.7, jobseekers with varying levels of baseline confidence also vary across a range of other characteristics. Therefore, our design does not allow us to determine whether the heterogeneous effects result from differences in baseline beliefs or from other variations across the groups.

5 Conclusion

Unemployed workers tend to systematically overestimate their reemployment prospects. In this paper, we estimate the causal effect of a large-scale information treatment aimed at correcting these misperceptions.

We find that the information treatment effectively encourages jobseekers to deregister from unemployment, but the nature of these exits varies across different groups of workers. For older women and especially for young men, the additional unemployment exits primarily reflect that the information treatment *encourages* more intense job search and job finding. On the other hand, young women and older men tend to become *discouraged* and transition into other support programs that do not require job search, or exit the labor force, at least temporarily.

Overall, our results confirm that information policies designed to correct subjective beliefs can enhance job search outcomes. They also provide a cautionary tale, however: for workers with reasonably attractive alternatives to job search, the policies may result in discouragement and may weaken their labor market attachment.

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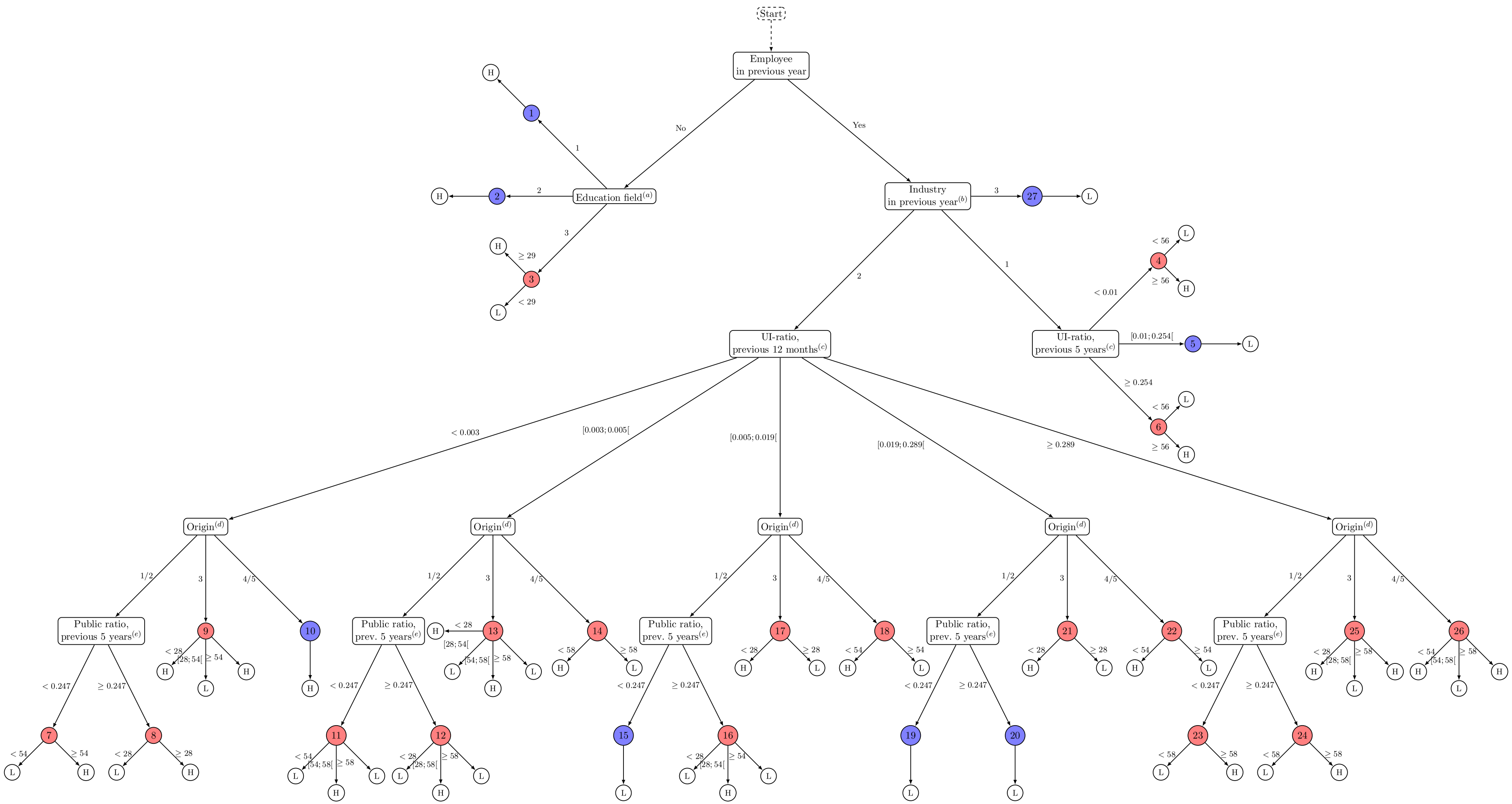
A Online Appendix

This Online Appendix provides supplementary information regarding the following aspects:

- Details on the profiling algorithm and the implementation of the RD design (Figure A.1 and Table A.1).
- A graphical illustration of the potential alternative treatment effects on job search (Figure A.2).
- Balancing tests examining the validity of the RD design (see Table A.2).
- Aggregate RD estimates in the pooled sample for different specifications (Table A.3).
- Specification tests for the RD estimates by socio-demographic subgroups (Table A.4).
- Results on additional outcome variables by socio-demographic subgroups (Table A.5).
- Results by baseline confidence groups (see Table A.6)
- Summary statistics by baseline confidence groups (Table A.7).
- Predictive power of the profiling tool information for unemployment duration (Table A.8)

Figure A.1: Illustration of Decision Tree and Partition into Subgroups



Note: The figure illustrates one version of the decision tree underlying the profiling algorithm. The sample is partitioned into 27 subgroups (based on all inputs except age), each represented by a colored dot. Blue dots represent subgroups with no age cut-off and red dots represent subgroups with at least one age cutoff. Each of the red subgroups are further partitioned into risk groups represented by white dots, where H denotes high-risk and L denotes low-risk job seekers. A further description for each of the 27 subgroups is presented in Table A.1.

$^{(a)}$ *Education field:* 1 - humanities, religion, aesthetic or missing education; 2 - social work, office, non-commercial, or pedagogical training, fishery, agriculture or food, scientific education 3 - Manufacturing and crafts, health, transportation and communications

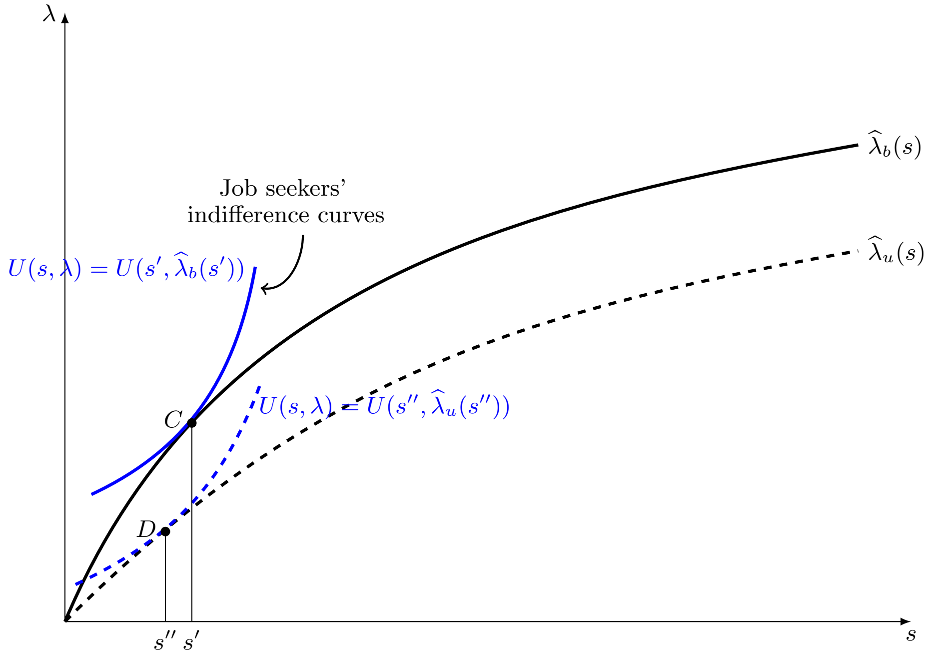
$^{(b)}$ *Industry categories:* 1 - public administration, health, teaching, employed in unknown activity, manufacturing, mining and quarrying, utilities, agriculture, forestry or fishery; 2 - trade, logistics, business services, culture, leisure or other services, real estate, information and communication, financial or insurance services. 3 - Construction

$^{(c)}$ *UI benefit ratio* is defined as the fraction of days receiving UI benefits in the previous 12 months and five years, respectively.

$^{(d)}$ *Origin categories:* 1 - Danish, 2 - descendent (Western country), 3 - immigrant (Western country), 4 - descendent (non-Western country), 5 - immigrant (non-Western country)

$^{(e)}$ *Public benefit ratio* is defined as the fraction of days receiving any public transfers in the previous five years.

Figure A.2: Graphical Illustration of Potential Alternative Treatment Effects on Job Search



Note: The figure illustrates how the information treatment potentially encourages job seekers to lower their search effort, s (depicted on the x-axis). The information treatment reduces the perceived job finding rate from $\widehat{\lambda}_b(s)$ (black solid line) to $\widehat{\lambda}_u(s)$ (black dashed line). For the job seeker characterized by the blue indifference curves, this induces a reduction in the optimal effort level from s' to s''. The overall value of being on UI is reduced from $U(s,\lambda) = U(s', \widehat{\lambda}_b(s'))$ to $U(s,\lambda) = U(s'', \widehat{\lambda}_u(s''))$. This graphical representation complements the upper panel of Figure 3, which depicts the scenario where the information treatment induces an increase in the optimal effort level.

Table A.1: Subgroups in the Representation of the Decision Tree Isolating Age Cutoffs

Subgroup	Employee in previous year	Former industry[(a)]	Education field[(b)]	UI benefit ratio 5 years[(c)]	UI benefit ratio 12 months[(c)]	Public benefit ratio 5 years[(d)]	Origin[(e)]	Age-induced treatment	Observations (+/- 3 years)[(f)]
1	No	0	1	-	-	-	-	-	-
2	No	0	2	-	-	-	-	-	-
3	No	0	3	-	-	-	-	Age >29	905
4	Yes	1	-	ratio <0.001	-	-	-	Age >56	2456
5	Yes	1	-	0.001 <ratio <0.254	-	-	-	-	-
6	Yes	1	-	ratio >0.254	-	-	-	Age >56	910
7	Yes	2	-	-	ratio <0.003	ratio <0.246	1	Age >54	2559
8	Yes	2	-	-	ratio <0.003	ratio >0.246	1	Age >28	552
9	Yes	2	-	-	ratio <0.003	-	2	Age <28 or Age >54	1072 ; 144
10	Yes	2	-	-	ratio <0.003	-	3	-	-
11	Yes	2	-	-	0.003 <ratio <0.004	ratio <0.246	1	54 <Age <58	36 ; 32
12	Yes	2	-	-	0.003 <ratio <0.004	ratio >0.246	1	28 <Age <58	10 ; 13
13	Yes	2	-	-	0.003 <ratio <0.004	-	2	Age <28 or 54 <Age <57	19 ; 0 ; 1
14	Yes	2	-	-	0.003 <ratio <0.004	-	3	Age <58	4
15	Yes	2	-	-	0.004 <ratio <0.018	ratio <0.246	1	-	-
16	Yes	2	-	-	0.004 <ratio <0.018	ratio >0.246	1	28 <Age <54	33 ; 27
17	Yes	2	-	-	0.004 <ratio <0.018	-	2	Age <28	60
18	Yes	2	-	-	0.004 <ratio <0.018	-	3	Age <54	14
19	Yes	2	-	-	0.018 <ratio <0.288	ratio <0.246	1	-	-
20	Yes	2	-	-	0.018 <ratio <0.288	ratio >0.246	1	-	-
21	Yes	2	-	-	0.018 <ratio <0.288	-	2	Age <28	192
22	Yes	2	-	-	0.018 <ratio <0.288	-	3	Age <54	76
23	Yes	2	-	-	ratio >0.288	ratio <0.246	1	Age >58	88
24	Yes	2	-	-	ratio >0.288	ratio >0.246	1	Age >58	247
25	Yes	2	-	-	ratio >0.288	-	2	Age <28 or Age >54	40 ; 12
26	Yes	2	-	-	ratio >0.288	-	3	Age <54 or Age >58	19 ; 15
27	Yes	3	-	-	-	-	-	-	-

Note: The table summarizes the 27 subgroups resulting from a partitioning of the full sample using all input variables and associated cutoffs *except age*.
[(a)] *Industry categories:* 1 - public administration, health, teaching, employed in unknown activity, manufacturing, mining and quarrying, utilities, agriculture, forestry or fishery; 2 - trade, logistics, business services, culture, leisure or other services, real estate, information and communication, financial or insurance services. 3 - Construction
[(b)] *Education categories:* 1 - humanities, religion, aesthetic or missing education; 2 - social work, office, non-commercial, or pedagogical training, fishery, agriculture or food, scientific education 3 - Manufacturing and crafts, health, transportation and communications
[(c)] *UI benefit ratio* is defined as the fraction of days receiving UI benefits in the previous 12 months and five years, respectively.
[(d)] *Public benefit ratio* is defined as the fraction of days receiving any public transfers in the previous five years.
[(e)] *Origin categories:* 1 - Danish, 2 - descendent (Western country), 3 - immigrant (Western country), 4 - descendent (non-Western country), 5 - immigrant (non-Western country)
[(f)] The last column reports the number of observations in our sample within a bandwidth of three years around the corresponding age cutoff.

Table A.2: Balancing Test: RD Regression for Pre-Determined Covariates

	Full sample		Men − young		Women − young		Men − old		Women − old	
	Coef.	P−value	Coef.	P−value	Coef.	P−value	Coef.	P−value	Coef.	P−value
Demographics										
Male	0.001	[0.961]	-	-	-	-	-	-	-	-
Danish citizen	-0.006	[0.663]	0.007	[0.922]	-0.051	[0.344]	-0.012	[0.584]	0.005	[0.776]
Migrant	0.006	[0.663]	-0.007	[0.922]	0.051	[0.344]	0.012	[0.584]	-0.005	[0.776]
Western origin	0.010	[0.260]	0.061	[0.177]	-0.012	[0.765]	-0.001	[0.957]	0.009	[0.481]
Married	-0.008	[0.727]	-0.003	[0.947]	-0.043	[0.482]	-0.020	[0.617]	0.010	[0.790]
Any children	-0.020	[0.720]	0.051	[0.702]	-0.090	[0.461]	-0.031	[0.755]	0.008	[0.923]
Expecting a child	0.002	[0.737]	-0.082	[0.216]	0.082	[0.080]	-0.003	[0.164]	0.000	[.]
Living in capital region	-0.008	[0.668]	-0.065	[0.442]	0.015	[0.829]	-0.027	[0.443]	-0.007	[0.823]
Level of education										
Primary or unknown	-0.008	[0.334]	0.007	[0.875]	-0.022	[0.462]	0.007	[0.636]	-0.017	[0.081]
Lower secondary	0.012	[0.499]	0.038	[0.549]	-0.018	[0.640]	0.030	[0.345]	0.032	[0.290]
Upper secondary	0.014	[0.558]	-0.067	[0.463]	0.029	[0.666]	-0.041	[0.302]	0.047	[0.226]
Short-cycle tertiary	-0.021	[0.080]	0.043	[0.489]	-0.009	[0.841]	-0.014	[0.454]	-0.049	[0.004]
Bachelor's degree (or equivalent)	-0.000	[1.000]	-0.095	[0.270]	0.050	[0.450]	0.002	[0.954]	0.011	[0.746]
Master's degree (or equivalent)	0.003	[0.837]	0.073	[0.287]	-0.031	[0.591]	0.017	[0.424]	-0.023	[0.158]
Field of education										
Humanities	0.005	[0.484]	0.009	[0.187]	0.031	[0.122]	-0.005	[0.549]	0.008	[0.548]
Manufacturing, craft	0.002	[0.849]	0.079	[0.428]	-0.135	[0.014]	0.010	[0.598]	-0.006	[0.606]
Natural science	-0.002	[0.841]	-0.000	[0.908]	-0.017	[0.170]	-0.002	[0.932]	0.001	[0.962]
Pedagogical	0.008	[0.539]	0.007	[0.317]	-0.006	[0.157]	0.033	[0.111]	-0.006	[0.833]
Social science, administration, trade	-0.012	[0.434]	-0.077	[0.175]	-0.013	[0.716]	-0.056	[0.043]	0.006	[0.819]
Health	-0.013	[0.355]	0.015	[0.819]	0.015	[0.842]	-0.000	[0.983]	0.004	[0.829]
Transport and communication	0.003	[0.718]	-0.001	[0.989]	0.062	[0.073]	-0.005	[0.681]	-0.008	[0.065]
Agriculture	-0.002	[0.596]	0.000	.	-0.002	[0.467]	0.011	[0.314]	-0.014	[0.008]
Labor Market Histories (26 weeks prior to survey)										
Employed	-0.009	[0.682]	-0.097	[0.297]	-0.016	[0.776]	-0.034	[0.250]	0.015	[0.651]
Unemployment benefits	0.006	[0.302]	-0.007	[0.773]	0.011	[0.357]	-0.001	[0.938]	0.006	[0.554]
Parental benefits	-0.013	[0.114]	0.014	[0.215]	-0.028	[0.673]	-0.001	[0.317]	-0.000	[0.695]
Sickness benefits	-0.011	[0.471]	0.026	[0.364]	-0.073	[0.113]	0.013	[0.576]	-0.026	[0.375]
Previous industry										
Business services	-0.002	[0.873]	0.114	[0.037]	0.043	[0.292]	-0.034	[0.187]	-0.019	[0.398]
Finance and insurance	-0.008	[0.321]	-0.003	[0.878]	0.001	[0.848]	-0.030	[0.030]	-0.007	[0.639]
Trade and transportation	-0.021	[0.252]	-0.165	[0.069]	0.003	[0.956]	-0.023	[0.498]	-0.013	[0.649]
Manufacturing	-0.000	[0.990]	0.000	.	0.000	.	-0.005	[0.882]	0.010	[0.691
Information, communication	0.011	[0.214]	-0.028	[0.411]	-0.021	[0.295]	0.028	[0.151]	0.010	[0.463]
Culture, leisure, other service	-0.013	[0.093]	-0.021	[0.303]	-0.019	[0.400]	0.004	[0.817]	-0.015	[0.192]
Public administration, education, health	0.023	[0.273]	0.000	.	0.000	.	0.019	[0.551]	0.024	[0.533]
obs	9,080	.	517	.	906	.	3,862	.	3,637	.

Note: This table reports regression coefficients using pre-determined covariates (measured at the time of the survey) as the dependent variable in RD regressions. We include observations within the subgroup-specific "optimal bandwidth" around the age cutoff (determined based on the main outcome, "unemployed at week 26 after survey") and weight observations using a triangular kernel. Separate tests are conducted for each variable. P−values are shown in square brackets.

Table A.3: RD Estimates: Effect of Information Treatment on Risk of Long-Term Unemployment

Dependent variable	Receiving Unemployment Benefits 26 Weeks after Survey[(a)]			
	(1)	(2)	(3)	(4)
A. Intention-to-treat effect	-0.068***	-0.069***	-0.080***	-0.068**
	(0.023)	(0.023)	(0.028)	(0.031)
B. Local average treatment effect				
First stage	0.867***	0.865***	0.849***	0.826***
	(0.011)	(0.011)	(0.014)	(0.016)
Second stage	-0.079***	-0.080***	-0.094***	-0.082***
	(0.026)	(0.027)	(0.033)	(0.038)
Mean dependent variable	0.427	0.427	0.427	0.427
No. of effective observation	9,396	8,994	13,554	5,024
Control variables	Yes	No	Yes	Yes
Optimal bandwidth	Yes	Yes	Yes	No
Polynomial	1	1	1	2
Bandwidth left (in weeks)	161	148	219	75
Bandwidth right (in weeks)	111	113	147	75
Robust 90% confidence intervals				
Intention-to-treat effect	[-0.128 ; -0.015]	[-0.129 ; -0.014]	[-0.128 ; -0.017]	[-0.100 ; 0.054]
Local average treatment effect	[-0.151 ; -0.020]	[-0.153 ; -0.021]	[-0.170 ; -0.023]	[-0.127 ; 0.059]

Note: The table reports the effects of the information treatment on the likelihood of receiving unemployment benefits 26 weeks after completing the survey for different RD regressions. In specifications (1)–(3), we rely on the optimal bandwidth selector that reduces the mean squared error (Cattaneo et al., 2017) above and below the cutoff. In specification (1), (2) and (4), we account for a set of covariates including socio demographics (gender, origin, marital status, number of children, living in capital region), level and field of education, and labor market histories (average monthly working hours and earnings in the year prior to job loss, UI fund association, employment 6 months and receipt of parental leave/sickness benefits 26 weeks prior to job loss), . In specification (3), we use a quadratic (2^{nd} order polynomial) instead of a linear specification. Standard errors are reported in parentheses. ***/**/* indicates statistical significance at the 1%/5%/10%-level, respectively.

[(a)]Includes public benefits subject to job search requirements, for example unemployment insurance (UI) benefits and social assistance.

Table A.4: Heterogeneous Effects of Information Treatment on Benefit Take-Up – Subgroup- and Outcome-specific Optimal bandwith

	Men – young (1)	Women – young (2)	Men – old (3)	Women – old (4)
Panel A: Benefit take-up 26 weeks after survey completion				
Unemployment benefits$^{(a)}$	-0.297***	-0.046	-0.019	-0.089**
	(0.095)	(0.074)	(0.041)	(0.039)
Education support	0.057**	-0.022	-0.001	0.003
	(0.025)	(0.029)	(0.003)	(0.007)
Sickness benefits	0.005	0.008	0.045**	0.031
	(0.023)	(0.033)	(0.022)	(0.022)
Parental leave	0.006	0.069***	0.000	0.000
	(0.007)	(0.025)	(.)	(.)
No public benefits$^{(b)}$	0.217**	-0.027	-0.011	0.068**
	(0.092)	(0.085)	(0.040)	(0.034)
hereof paid employment$^{(c)}$	0.071	-0.111*	-0.061	0.050
	(0.084)	(0.065)	(0.042)	(0.032)
hereof other self-support$^{(d)}$	0.051	0.081	0.045	0.015
	(0.058)	(0.049)	(0.030)	(0.018)
Panel B: Benefit take-up 52 weeks after survey completion				
Unemployment benefits$^{(a)}$	-0.127*	0.061	-0.031	-0.019
	(0.070)	(0.068)	(0.037)	(0.031)
Education support	0.041	-0.034	-0.002	-0.005
	(0.036)	(0.030)	(0.002)	(0.008)
Sickness benefits	-0.074*	-0.055	0.003	-0.015
	(0.044)	(0.038)	(0.017)	(0.017)
Parental leave	-0.005	0.089**	0.000	0.000
	(0.007)	(0.037)	(.)	(.)
No public benefits$^{(b)}$	0.162*	-0.080	0.030	0.029
	(0.093)	(0.079)	(0.036)	(0.030)
hereof paid employment$^{(c)}$	0.123	-0.104	-0.003	0.007
	(0.092)	(0.082)	(0.037)	(0.030)
hereof other self-support$^{(d)}$	0.022	-0.030	0.035	0.034*
	(0.065)	(0.041)	(0.023)	(0.020)

Note: The table reports intention-to-treat effects of the information treatment based on RD regressions for various subgroups. The young sample includes men and women facing age cutoffs in their late twenties (age 28 or 29). The old sample includes men and women facing age cutoffs in their mid-fifties (age 54 or 56). We include observations within the "optimal bandwidth" around the age cutoff and weight observations using a triangular kernel. The "optimal bandwidth" is subgroup and outcome specific. In all specifications, we include controls for predetermined individual characteristics, including number of children, marital status, level of education, average monthly working hours and earnings in the year prior to job loss, and previous industry. For the young sub-groups (men and women), we additionally control for whether the individual is expecting a child at the time of the survey. Standard errors are reported in parentheses. ***/**/* indicates statistical significance at the 1%/5%/10%-level, respectively.

$^{(a)}$The measure is equal to one if the individual receives public benefits subject to job search requirements, that is, unemployment insurance (UI) benefits or social assistance.

$^{(b)}$The measure is equal to one if the individual does not receive any public benefit payments in the corresponding week. This includes paid employment, self-employed, being out of the labor force or having move abroad.

$^{(c)}$The measure is equal to one if the individual is paid employed (only observed at the monthly level) and does not receive public benefits in the corresponding month.

$^{(d)}$The measure is equal to one if the individual is not paid and and does not receive public benefits in the corresponding month.

Table A.5: Effect of Information Treatment on Additional Outcome Variables

	Men – young (1)	Women – young (2)	Men – old (3)	Women – old (4)
A. Labor market outcomes (cumulated within 12 months)				
Total working hours within 12 months	193.04	-35.46	-36.18	40.54
	(121.70)	(86.91)	(53.64)	(44.37)
Total labor earnings within 12 months in DKK1,000	26.67	-14.30	-4.51	5.93
	(24.56)	(15.68)	(12.71)	(8.59)
B. Caseworker-related outcomes (within 6 months)				
Any ALMP participation	-0.101	-0.004	-0.008	-0.018
	(0.101)	(0.076)	(0.041)	(0.038)
No. of caseworker meetings/week	0.010	0.006	-0.004	0.008
	(0.020)	(0.015)	(0.008)	(0.007)
No. of observation	454	823	3629	3557
Bandwidth	[-70:120]	[-87:121]	[-224:91]	[-138:78]

Note: The table reports intention-to-treat (ITT) effects of the information treatment on additional outcome variables based on RD regressions for various subgroups. The young sample includes men and women facing age cutoffs in their late twenties (age 28 or 29). The old sample includes men and women facing age cutoffs in their mid-fifties (age 54 or 56). We include observations within the "optimal bandwidth" around the age cutoff and weight observations using a triangular kernel. The "optimal bandwidth" is sub-group specific, and obtained based on the outcome variables "receiving UI benefits 26 weeks after survey completion". In all specifications, we include controls for predetermined job seeker characteristics, including number of children, marital status, level of education, average monthly working hours and earnings in the year prior to job loss, and previous industry. For the young sub-groups (men and women), we additionally control for whether the individual is expecting a child at the time of the survey. Standard errors are reported in parentheses. ***/**/* indicates statistical significance at the 1%/5%/10%-level, respectively.

Table A.6: Heterogeneous effects of information treatment by baseline confidence

	Men – young			Women young		
	Full	Baseline confidence		Full	Baseline confidence	
	sample	High	Moderate	sample	High	Moderate
	(1)	(2)	(3)	(4)	(5)	(6)
Benefit take-up 26 weeks after survey completion						
Unemployment benefits[(a)]	-0.297***	-0.159	-0.288**	-0.046	0.146	-0.095
	(0.095)	(0.113)	(0.127)	(0.074)	(0.114)	(0.094)
Education benefits	0.068**	0.061	0.050	-0.024	-0.097**	0.010
	(0.031)	(0.046)	(0.044)	(0.031)	(0.044)	(0.040)
Sickness benefits	-0.000	0.040*	-0.035	0.009	0.012	-0.018
	(0.024)	(0.024)	(0.035)	(0.033)	(0.076)	(0.036)
Parental benefits	0.006	0.018	-0.005	0.059**	0.039	0.045
	(0.007)	(0.012)	(0.005)	(0.024)	(0.037)	(0.029)
No public benefits[(b)]	0.223**	0.040	0.278**	0.001	-0.100	0.059
	(0.096)	(0.114)	(0.131)	(0.073)	(0.139)	(0.095)
hereof paid employment[(c)]	0.142	-0.087	0.272**	-0.094	-0.227*	0.006
	(0.095)	(0.119)	(0.121)	(0.065)	(0.130)	(0.085)
hereof other self-support[(d)]	0.081	0.128**	0.006	0.095**	0.131*	0.053
	(0.070)	(0.056)	(0.106)	(0.046)	(0.075)	(0.061)
No. of observation	454	308	239	823	264	493
Bandwidth	[70:120]	[100:154]	[90:111]	[87:121]	[48:112]	[85:135]
	Men – old			**Women – old**		
	Full	Baseline confidence		Full	Baseline confidence	
	sample	High	Moderate	sample	High	Moderate
	(7)	(8)	(9)	(10)	(11)	(12)
Benefit take-up 26 weeks after survey completion						
Unemployment benefits[(a)]	-0.019	-0.052	-0.012	-0.089**	-0.062	-0.104**
	(0.041)	(0.049)	(0.060)	(0.039)	(0.054)	(0.047)
Education benefits	-0.001	0.004	-0.008*	0.001	-0.005	0.004
	(0.003)	(0.004)	(0.005)	(0.006)	(0.005)	(0.008)
Sickness benefits	0.035*	0.050**	0.025	0.021	0.059*	-0.006
	(0.018)	(0.021)	(0.028)	(0.020)	(0.033)	(0.022)
Parental benefits	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(.)	(.)	(.)	(.)	(.)
No public benefits[(b)]	-0.016	-0.001	-0.006	0.067*	0.008	0.106**
	(0.041)	(0.050)	(0.059)	(0.038)	(0.056)	(0.047)
hereof paid employment[(c)]	-0.055	-0.046	-0.032	0.053	0.005	0.076*
	(0.040)	(0.053)	(0.057)	(0.038)	(0.055)	(0.045)
hereof other self-support[(d)]	0.045*	0.043	0.039	0.015	0.002	0.030
	(0.026)	(0.030)	(0.040)	(0.022)	(0.029)	(0.027)
No. of observation	3,629	2,127	1,463	3,557	2,224	2,202
Bandwidth	[224:91]	[230:120]	[181:90]	[138:78]	[224:79]	[128:101]

Note: The table reports intention-to-treat (ITT) effects of the information treatment based on RD regressions for subgroups classified based on gender and age (see notes of Table 1 for details) with varying levels of baseline confidence. "High confidence" means that individuals expect to find employment within the next three months. "Moderate confidence" means that individuals expect it to take more than three months to secure a job, or that they acknowledge uncertainty. The "optimal bandwidth" is sub-group specific, and obtained based on the outcome variables "receiving unemployment benefits 26 weeks after survey completion". In all specifications, we include controls for predetermined job seeker characteristics, including number of children, marital status, level of education, average monthly working hours and earnings in the year prior to job loss, and previous industry. For the young sub-groups (men and women), we additionally control for whether the individual is expecting a child at the time of the survey. Standard errors are reported in parentheses. ***/**/* indicates statistical significance at the 1%/5%/10%-level, respectively.
[(a),(b),(c),(d)] See notes for Table 1.

Table A.7: Summary Statistics by Baseline Confidence

	Men – young			Women – young		
	Baseline confidence			Baseline confidence		
	Moderate	High	Difference	Moderate	High	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Married	0.09	0.06	0.03	0.26	0.17	0.10***
Number of children	0.33	0.36	-0.03	0.94	0.79	0.15**
Expecting a child	0.06	0.07	-0.01	0.13	0.04	0.09***
Living in capital region	0.29	0.24	0.05	0.24	0.35	-0.11***
Level of education						
Primary education or unknown	0.06	0.02	0.05**	0.03	0.02	0.01
Lower secondary education	0.10	0.13	-0.03	0.08	0.07	0.01
Upper secondary education	0.35	0.40	-0.05	0.30	0.32	-0.02
Short cycle tertiary education	0.12	0.15	-0.02	0.07	0.08	-0.01
Bachelor's degree (or equivalent)	0.22	0.22	0.00	0.34	0.37	-0.03
Master's degree (or equivalent)	0.14	0.09	0.05*	0.18	0.13	0.05*
Labor market outcomes in last years						
Any employment	0.40	0.34	0.06	0.23	0.27	-0.04
Avg. monthly working hours	45.64	38.58	7.07	22.42	28.09	-5.67
Avg. monthly labor earnings (in DKK1,000)	7.25	6.31	0.94	3.15	4.31	-1.15**
No. of observation	221	233	454	466	357	823
	Men – old			Women – old		
	Baseline confidence			Baseline confidence		
	Moderate	High	Difference	Moderate	High	Difference
	(7)	(8)	(9)	(10)	(11)	(12)
Married	0.56	0.56	-0.01	0.60	0.56	0.04**
Number of children	1.64	1.71	-0.06	1.76	1.79	-0.03
Expecting a child	0.00	0.00	0.00	0.00	0.00	0.00
Living in capital region	0.27	0.22	0.05***	0.23	0.21	0.02
Level of education						
Primary education or unknown	0.03	0.02	0.01	0.02	0.01	0.02***
Lower secondary education	0.17	0.17	0.00	0.18	0.15	0.03**
Upper secondary education	0.46	0.52	-0.06***	0.47	0.48	-0.01
Short cycle tertiary education	0.08	0.08	0.00	0.06	0.06	0.00
Bachelor's degree (or equivalent)	0.16	0.13	0.03**	0.20	0.25	-0.04***
Master's degree (or equivalent)	0.10	0.08	0.02**	0.07	0.06	0.01
Labor market outcomes in last years						
Any employment	0.97	0.98	-0.01***	0.94	0.95	-0.01
Avg. monthly working hours	127.48	134.42	-6.94***	110.84	117.13	-6.29***
Avg. monthly labor earnings (in DKK1,000)	35.33	36.38	-1.06	24.03	25.97	-1.94***
No. of observation	1,733	1,896	3,629	2,059	1,498	3,557

Note: The table reports summary statistics for subgroups classified based on gender and age with varying levels of baseline confidence. "High confidence" means that individuals expect to find employment within the next three months. "Moderate confidence" means that individuals expect it to take more than three months to secure a job, or that they acknowledge uncertainty. We include observations within the optimal bandwidth (based on the outcome "receiving unemployment benefits 26 weeks after survey completion") around the age cutoff and weight observations using a triangular kernel. ***/**/* indicates statistical significant differences at the 1%/5%/10%-level, respectively. Percentage shares unless indicated otherwise.

Table A.8: Predictive power of profiling information in pre-intervention period (April 2014 to June 2015)

Dependent variable	Receiving unemployment benefits in week 26		
	(1)	(2)	(3)
Predicted to be at-risk	0.068***		0.054***
	(0.011)		(0.011)
Baseline belief about job finding			
within 1 month		-0.216***	-0.209***
		(0.022)	(0.022)
within 3 months		-0.151***	-0.143***
		(0.014)	(0.014)
within 6 months		-0.056***	-0.051***
		(0.016)	(0.016)
more than 6 months		0.026	0.021
		(0.035)	(0.035)
already found a job		-0.331***	-0.323***
		(0.042)	(0.042)
other[a]		-0.287***	-0.307***
		(0.049)	(0.049)
Constant	0.439***	0.560***	0.530***
	(0.008)	(0.010)	(0.011)
No. of observations	7,930	7,930	7,930
R2 (standard)	0.005	0.028	0.031
R2 (out-of-sample)	0.005	0.028	0.031

Note: The table illustrates the predictive power of the profiling information in a sample of jobseekers in the pre-intervention period (April 2014-June 2015) when no UI recipients received the information treatment. Otherwise, we apply the same sample restrictions as for main analysis sample including individuals who would be within six years of the relevant age cutoff if the information treatment had been in place. The columns show linear regressions where the outcome variable is a dummy for remaining unemployed after 26 weeks and where the explanatory variables are various dummies: *Predicted to be at-risk* represents a dummy for being predicted as being at "high risk" of long-term unemployment (>26 weeks) according to the profiling tool (e.g. this is the information contained in the information treatment). *Baseline belief*-dummies correspond to survey answers to the question "How quickly do you think you will get a job?", with "I don't know" as the omitted category. ***/**/* indicates statistical significance at the 1%/5%/10%-level, respectively. To provide a valid measure of whether adding additional variables improves predictive accuracy, the table includes an out-of-sample R^2 computed via 5-fold cross validation.