# Advising Job Seekers in Occupations with Poor Prospects: A Field Experiment

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**PRELIMINARY - PLEASE DO NOT CITE**

**Abstract**

We study the impact of online information provision to unemployed job seekers who are looking for work in occupations with poor labor market prospects. Job seekers received online suggestions about suitable alternative occupations, and how the prospects of these alternatives compare to the job seekers' current occupation of interest. Some additionally received a link to a motivational video. We evaluate the interventions using a randomized field experiment covering all registered job seekers in the target occupations, where two thirds are treated. The vast majority of job seekers open the message revealing the alternative suggestions. The motivational video link is rarely used. Effects on unemployed job seekers in structurally poor labor markets are large: their employment, hours of work and labor income all improve by 4% to 5%, with persistent impact over 1.5 years. Additional survey evidence shows that treated job seekers find employment in more diverse occupations.

**Keywords**: Job search, occupational mobility, randomized experiment, information treatment
**JEL codes**: J62, J64, C93

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# 1 Introduction

Occupational transitions play a significant role in labor market adjustments to changes in the economy. The Covid-19 pandemic, technological development, and automation have been associated with profound changes in the demand for certain occupations.[1] Adjusting to such a changing environment means that workers need to transit from occupations in decline to occupations with better prospects. A major challenge is that workers may not be well informed about occupations they could or should consider. Moreover, even if well informed, there may be psychological hurdles to consider an occupational change. The lack of familiarity and uncertainty about the fit of one's skills with the skills needed in other occupations may constitute significant hurdles to occupational transitions. Evidence indeed suggests that when searching for jobs, individuals tend to narrowly focus on occupations in which they have experience (Belot et al., 2019; Faberman and Kudlyak, 2019), and this can be problematic when these occupations are in low demand.

In this paper, we evaluate a low-cost and carefully designed digital intervention aimed at unemployed job seekers who are looking for work in occupations that are in low demand. The intervention aims at addressing informational deficits about job prospects in search occupations and alternative occupations. We designed and conducted the intervention in collaboration with the Dutch Public Employment Service (UWV). The experiment involved 30,129 unemployed job seekers who recently became unemployed and searched in one of 21 occupations with poor employment prospects.

In our jointly designed intervention, the Public Employment Service informed 20,125 of these job seekers about the poor job prospects in their primary occupation of interest and suggested alternative occupations with better prospects that are particularly well-suited to their skills background. Each suggested occupation is displayed alongside information about the job finding prospects, the skills required to do well in the occupation, and a link to a webpage with more detailed information about the occupation. To ensure that the occupational suggestions we make are realistic switches for the targeted job seekers, our suggestions are based on the most common occupational transitions observed from millions of resumes from former job seekers that we cross-checked to be representative for

[1] For the Covid-Pandemic, see, e.g., del Rio-Chanona et al. (2020); Forsythe et al. (2020). For technological development and automation see, e.g., Autor et al. (2003); Autor (2015); Brynjolfsson et al. (2018); Frey and Osborne (2017).

occupation mobility of the Dutch labor force. From these common and attainable transitions, we include those that currently offer sufficiently good job finding prospects. The experiment also includes an additional motivational component for a third of the participants. These participants received a link to a short video where people who recently made a successful transition from one occupation to another shared their positive experience.

More than 64% of the treatment group opened the informational message. A sizeable share also clicked on at least one occupational suggestion for more information. The motivational video, however, was rarely watched, so this treatment group is effectively only exposed to the information part of the treatment.

Our main analysis focuses on the sample of job seekers without paid employment at the time of the intervention and were searching in an occupation that had structurally poor prospects (around 10,000 job seekers). Because of the timing of the intervention (spring of 2021), a number of occupations had 'temporarily' poor prospects due to restricted economic activities from the Covid-19 pandemic, and we report results for job seekers searching in these occupations separately. The remaining group (job seekers who were partially employed at the time of the intervention) is also interesting to study, but one may expect the intervention to affect them differently.[2]

Our key outcomes of interest are the job finding probability, labor earnings, hours worked, and benefits received (all measured from administrative data). Further administrative data from online search records and caseworkers records allows us to investigate job search activities. In addition, we assess how the intervention impacts job search activities and labor market beliefs, using survey data collected before and after the interventions.

The survey data shows that job seekers are, on average, willing to consider alternative occupations and confident that they will be able to do well in alternative occupations. However, job seekers are generally not aware of how poor the job prospects are in their primary occupation of interest, compared to suitable alternatives. While most job seekers do consider one (or a couple of) alternative occupations, their assessment of the job finding chances in these alternatives is hardly correlated with true job finding prospects. These findings point towards fertile grounds for our information intervention. Note that we do not force unemployed job seekers to broaden their job search: suitable switches with better

[2]We report results for job seekers in temporarily poor occupations and for partially employed job seekers in section 6.2.4.

prospects are only suggested to them. As shown in van der Klaauw and Vethaak (2022), forcing a broader job search, especially without adequate guidance, could backfire and reduce job finding rates.

The effects of the information we provide to unemployed job seekers in structurally poor labor markets are large: employment increased by 5%, hours worked by 4.5% and earnings by 4% relative to the control group. Effects are persistent over 1.5 years. The effects on employment are large, and do not seem to be associated with lower hours or lower wages so that employment effects carry over to hours worked and earnings. In the Netherlands, unemployment benefits are not cut one-for-one with income in order to provide incentives to take low-paying or low-hour jobs, and the reductions in the receipt of unemployment benefits we find are therefore smaller and insignificant. In line with the nature of our information treatment, we find in our survey that individuals in the treatment group who found a job report a significantly lower probability to work in their primary search occupation relative to those in the control group, and instead report a larger share of employment in the recommended occupations as well as in other occupations.

Our study contributes to a recent and growing literature on the effectiveness of targeted and tailored recommendations on job search behavior and labor market outcomes (Belot et al., 2019, 2022; Altmann et al., 2022; Le Barbanchon et al., 2023; Ben Dhia et al., 2022), which we discuss in more detail in Section 2. The current study is of a much larger scale than Belot et al. (2019) and Belot et al. (2022), it focuses on job seekers searching in occupations with poor prospects (in contrast to Altmann et al. (2022)), and evaluates the effects on finding employment, including the type of occupation. The intervention we propose here is not embedded in a job search platform or an 'automated recommendation system'. It therefore decouples the informational aspect, which can be used broadly in searching for jobs, from the saliency effect associated with specific vacancies being made more salient when searching for jobs. Here the idea is to induce a change in the general 'job search strategy'. Contrary to Le Barbanchon et al. (2023) our occupational suggestions do not rely on Machine Learning technology using search behavior as input, but they are based on observed recent successful occupational transitions. As such, our algorithm is designed to encourage the exploration of jobs that may not come to mind, in contrast to machine learning algorithms that are based on past search behavior and do not encourage exploration (Li et al. (2020)). This encouragement to explore beyond job seekers'

own search patterns is particularly relevant to those individuals most in need of alternative suggestions as they are better off moving away from the structural low demand in their occupation.

The integrated design of the intervention, both in terms of individualizing publicly available information and in terms of the carefully designed message provide relevant and immediately applicable policy insights. As it is easy to implement, this intervention highlights a promising avenue to help job seekers in slack labor markets, a core task of Public Employment Services.

The rest of the paper is structured as follows. In Section 2 we review the recent literature. In 3, we describe the institutional context of our experiment. Section 4 describes the experimental design. We provide descriptive results regarding job search behavior of our sample (based on a pre-intervention survey) in Section 5. In Section 6 we present our empirical evaluation of the impact of the intervention using both administrative and survey data. Section 7 concludes.

# 2 Related Literature

The study contributes to a number of studies targeting information frictions in the labor market. Belot et al. (2019) design and test a recommendation system aimed at broadening the set of occupations considered. The experiment was conducted on a small sample (300) of UK job seekers and included tailored occupational recommendations in an online job search platform. The authors observed job seekers' search behavior over the course of 3 months, and they found that personalized suggestions of alternative occupations affects job search and increases the chances of getting an interview. Belot et al. (2022), Bächli et al. (2025) and Altmann et al. (2022) evaluate recommendation systems aimed at broadening job search and suggesting alternative occupations on larger samples.

Belot et al. (2022) focus on a sample of long-term job seekers. The recommendations are also embedded in an online job search platform, and they find a large and positive impact on labor market outcomes (probability of finding a stable job). The effects they report, based on a sample of 800, are relatively large and possibly driven by the specific focus on long-term unemployed. Altmann et al. (2022) test a similar intervention in Denmark, although the suggestions are not directly linked to job ads, but instead appear in the job seeker portal at the employment agency. They also evaluate another intervention providing information about the number of available vacancies in occupations that fit the job

seeker's personal job search profile. The information provided is not one-off but is instead visible every time job seekers log into the portal. They also implement a clustered randomization, varying the intensity of treatment across regions, to evaluate possible negative spillover effects on non-treated job seekers, a concern that applies to experimental interventions targeting job seekers (Crépon et al., 2013; Gautier et al., 2018). They find significant and large effects of around 9% for working hours and earnings in the year after the intervention if less than 50% of the local population is treated. The effects are, however, canceled out in regions where the fraction of treated is higher. Interestingly they do not find negative spillover effects on non-treated job seekers. It appears that the job seekers in the treated group crowded each other in following the same new suggestions, but reduced the congestion in the occupations considered by the non-treated. Importantly, these interventions are not targeting occupations in tight markets. In contrast, a distinguishing and novel feature of our intervention is that it reallocates workers from slack markets to occupations in much tighter markets. In such setting, congestion effects are likely to be much smaller.

Bächli et al. (2025) propose and evaluates new approaches to recommendations of occupations. One approach is to recommend occupations based on past experience, the other is to recommend occupations based on the skills needed in that occupation. They build a job search platform and measure job seekers' skills that correspond to non-cognitive skills identified in the O*NET descriptors. In a sample of 1,250 participants, they find that both recommendation tools tend to improve job-finding rates, although the effects are only significant for some subgroups of job seekers, specifically those who transit out of occupations that were a poor match to their skills.

Our study also relates to recent work by Le Barbanchon et al. (2023) who embed an AI-based recommendation system, and Behaghel et al. (2022) who encourage job seekers to use a system that predicts which firms are likely to recruit in the near future. These studies use prediction algorithms to recommend suitable opportunities. Le Barbanchon et al. (2023) implements a two-sided experiment on the job search platform of the Swedish Public Employment Service, where half of the vacancies and job seekers are treated. Some labor markets are left out as supercontrols. They find positive but small effects on the probability of employment (0.6%) among treated individuals after six months, and small and insignificant general equilibrium effects. The intervention designed by Behaghel et al. (2022) intends, like in our study, to move individuals from slack to tight

labor markets. They find small positive effects, which they hypothesize could be due to the design which provides the information in an email, rather than directly at the stage of job search. As mentioned earlier, an important difference between our approach and the AI-based approach is that our algorithm aims at encouraging the exploration of jobs that do not come to mind. In contrast, AI-based approaches usually use past search behavior as an input, which limits exploration of very different alternatives. Our approach also used information from successful *transitions* rather than data on search behavior. It is possible to alter AI-based algorithms to force more exploration, as shown in Li et al. (2020), but it remains challenging to identify *feasible* transitions without information on actual matches.

Lastly, Ben Dhia et al. (2022) also evaluate an intervention aimed at providing assistance and advice using online tools. Job seekers receive online personalized advice on sectors and geographic locations; step-by-step planning assistance; regular reminders and encouragement messages; and general tips, such as how to behave during a job interview. The advice touches on a much larger range of aspects of job search. Effects in their setting are very small or absent.

To summarize, our main contribution to literature lies in the fact that (1) we designed a novel intervention and evaluate it with a large scale experiment; (2) we focus on job seekers searching in particularly challenging markets; (3) we provide one-off advice about potentially viable *search strategies*; and (4) we base this advice on data from recent successful transitions. We provide job seekers with truthful information about the poor probability of finding employment in their primary search occupation (this relates to push factors), and provide alternatives to them for occupations with promising prospects (pull factors). Also, in contrast to Ben Dhia et al. (2022), we do not provide feedback on search behavior, but focus on information on labor demand and our recommendations are based on actual tightness information. We provide the information in a way that is designed to be intuitive and easy to understand, and that is part of the existing way of working at the Public Employment Service. While less sophisticated than information embedded directly in a job search platform, an information message is very easy to implement and adjust to reflect relevant changes in the labor market. It also requires minimal digital competency, which is likely to be relevant when targeting such sample of job seekers.

# 3 The Dutch Institutional Context

Unemployment rates in the Netherlands are relatively low (4.22% in 2021) compared to the US (5.37%) and the OECD average (6.16%).[3] The Dutch Public Employment Service's core responsibility is the administration and payment of employee insurances, including unemployment benefits. In the Netherlands, individuals can apply for unemployment benefits if they meet all of the following criteria: they are insured for unemployment, their hours of work are decreased by more than five hours per week, they are available to start a different job immediately, they have worked at least 26 out of the last 36 weeks, and their transition to unemployment was not their own fault. The unemployed need to register with the Dutch Public Employment Service in order get access to unemployment benefits.[4] Upon registration, unemployed get access to an online 'work folder' in which they register relevant information (such as CV) and a questionnaire about their previous job, personal situation and expectations about finding work. Unemployed job seekers can indicate up to three 'search occupations', i.e., occupations that the individual would like to find employment in. Unemployed job seekers have an incentive to report search occupations that are accessible to them in terms of their skills set, or with additional training (which we cannot monitor), because their search behavior is monitored by he Public Employment Service. Based on the information entered in the 'work folder', the Public Employment Service can offer help that best suits the unemployed's situation. This includes support online, by phone, and/or in person. Unemployed job seekers are expected to send 4 applications per 4 weeks. Job seekers will discuss their job search with work counselors. Much of this communication takes place online, via the 'work folder', and via email sent from that platform.

Another core task of the Public Employment Service is to assist job seekers in finding employment, particularly those with a large distance to the labor market. To this end, the employment office provides a number of services. While job seekers do get assigned a caseworker, the employment office also states that they "are calling on Dutch citizens to assume their own responsibility and on their self-reliance; the services we provide will increasingly be based on online self-service" (Uitvoeringsinstituut Werknemersverzekeringen , UWV). An important part of

[3]Data retrieved from https://data.oecd.org/unemp/unemployment-rate.htm on July, 12, 2023.

[4]Note that it is possible to work in a paid job while receiving unemployment benefits under certain conditions, e.g., partial unemployment

these 'online services' is the employment office's provision of two types of labor market information that we use in our experiment. Using data on the number of registered job seekers with a certain 'search occupation', as well as the number of available vacancies, the Public Employment Service assesses occupation-specific job prospects that they publish online.[5] The Public Employment Service also publishes a list the alternative occupations, i.e., occupational switches that job-seekers have actually made in recent years that is computed from CV data of all job seekers. This provides an inspiration for others who are looking for a new job.[6]. Both pieces of information are updated yearly, and we explain below how they are computed. While job seekers can consult labor market information on these two websites, it is scattered throughout the websites. Moreover, the websites is not personalized, meaning job seekers have to be well aware of their wants and needs to find relevant information. In our experiment, we (i) consolidate the available – and add new – labor market information about occupations, and (ii) provide this information in a personalized manner through email.

# 4 Experimental Design

## 4.1 Selection of occupations

As explained in Section 3, unemployed job seekers enter up to three 'search occupations' on the platform of the Public Employment Service. The aim of our experiment is to help unemployed job seekers who search in occupations with low employment prospects to consider different, more promising, occupations. Job seekers who search in these occupations are most likely to benefit from information on alternative occupations with better prospects.

To select occupations with poor job finding prospects, we use the 'job finding score'. The job finding score is a metric used by the employment office based on the ratio of vacancies to job seekers in the employment office's database and outflow rates of unemployment insurance recipients that is updated multiple times per year. These scores are computed for over 600 narrowly defined occupations (5-digit classification).[7] The score runs from 2 (very poor job prospects) to 10

[5]Via a website with information about which occupations are most in demand and for which there is lee work: https://www.werk.nl/arbeidsmarktinformatie/kansen-arbeidsmarkt

[6]https://www.werk.nl/arbeidsmarktinformatie/kansen-arbeidsmarkt/overstapberoepen-werk-vinden-in-ander-beroep

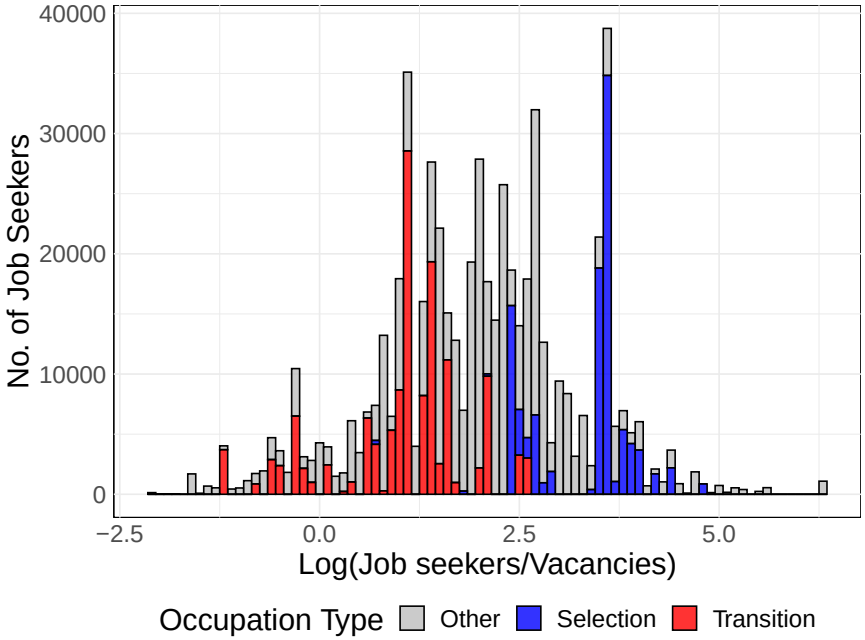
[7]The occupational classification used is called 'BRC+' which resembles the ISCO classification, but more detailed and slightly modified to better reflect the Dutch labor market.

(excellent job prospects). For the experiment, we selected all individuals interested in occupations with a score of 2, 3 or 4 in the spring of 2021, leading to 21 occupations (henceforth *selection occupations*). These 21 occupations exhibit a substantial variety in terms of their field (e.g., animal caretakers, waiters/bartenders, taxi drivers, graphic designer). While most of these occupations require a low or intermediate vocational education level, some, e.g., social workers, have higher requirements. The complete list can be found in Table 2 (including their relative share within the sample). Appendix Table A1 provides the original occupation names in Dutch.

We have access to all registered job seekers' records in the Netherlands and select all who have indicated on their CV that they are looking for a job in one of the 21 occupations with a very low job finding score. This implies that we also restrict our sample to job seekers who have completed their online CV, which automatically ensures a minimum level of computer skills. Given that we send our labor market information by email, this was desirable as we exclude those who may be less likely to read emails. Finally, we impose the restriction that, at the time of sample selection, job seekers should have at least one month of unemployment insurance benefits eligibility left, to ensure they would not automatically exit the sample before receiving the first information message.

To determine suitable alternative occupations (henceforth *transition occupations*) these job seekers can transition to, we consider two metrics: historical switches, and current labor market prospects. Data on historical occupational switches comes from resume data that the Public Employment Service collects for all registered job seekers. This allows us to identify the occupations that other job seekers with skills, experience and educational backgrounds similar to the job seekers in our data most often switch to. We are agnostic about how these transitions have occurred, but the fact that they do occur does mean it is easy enough to move from one occupation to the other. A concern with this approach is that the occupational transitions we observe from past stocks of unemployed might not be representative of occupational mobility in the full population. While our primary focus is on unemployed job seekers, using panel data from the Dutch Labor Force Survey, we do find that occupational mobility in the Dutch population is similar to that from the data of the Public Employment Service. In our list of suitable alternatives, we include only occupations with favorable current labor market prospects, as indicated by a job finding score of at least 6. Depending on a job seeker's preferred occupation, we selected 7 to 9 alternative occupations.

Figure 1: Labour market tightness of selection, transition and other occupations




The combination of these two criteria ensures that we send job seekers a list of occupations that (i) they are likely to be (or can easily become) qualified for and (ii) have good job finding prospects. While we generally selected occupations with the highest number of historical switches among those with sufficiently good job opportunities — presenting them in order of observed switch frequency — we allowed some leeway for the expertise of the Public Employment Service.

To put the differences in labor market prospects in perspective, Figure 1 shows the distribution of market tightness (the log of job seekers/vacancies) for selection, transition and other occupations.[8] The figure confirms the expected pattern: selection occupations have much higher job seeker to vacancy ratios than transition occupations. The average ratio for selection occupations is approximately 23, whereas it is below 2 for transition occupations. Data from the Dutch Labour Force Survey further shows that the occupations we suggest offer better wages, more often full-time hours and are less often jobs with temporary contracts compared to the selection occupations.

One final concern is that job seekers looking for work in our selection oc-

[8]These statistics are based on 'Open Match Data' published on April 13, 2021 by the Dutch Public Employment Service. These data contain information on the number of job seekers who have indicated to search for work (or have experience) in a certain occupation and the number of vacancies in these occupations. An important caveat is that job seekers may register in multiple occupations. As the data is available at the occupation level, we can not observe this.

cupations differ from those looking for work in transition occupations in ways that make them less attractive on the labor market. Tables A2 and A3 in the Appendix shows how job seekers looking for work or with experience in, respectively, our selection occupations differ from those in the transition occupations we selected, and all other occupations. There are a number of striking patterns. Educational attainment does not materially differ between job seekers in the different categories of occupations. We consider this to be encouraging, as it suggests that lack of educational attainment is not a barrier to transitions. With regards to geographical mobility, job seekers in our selection occupations have an equally sized search radius compared to those in transition occupations. We consider this another positive signal about the quality of our transition occupations, as it indicates that job seekers will not be forced to compete with others who are willing to consider a much larger set of jobs. In contrast, job seekers in other occupations are willing to search for work in geographically more distant places. Job seekers in our selection occupations further are younger on average, and less likely to be male than in transition and other occupations. Table A3 shows that there is no difference in experience between the selection occupations and transition occupations, despite the age difference; another positive signal for the feasibility of these transitions. In short, while job seekers looking for work in our selection occupations differ from those looking for work in transition occupations, they are equally educated, experienced, and willing to commute.

## 4.2 Interventions

Our intervention aims to ensure job seekers (i) are aware of the poor labor market prospects in their occupation of interest and (ii) learn about suitable alternative occupations.

We present the information through an information visualization that we designed together with the communication department of the Dutch Public Employment Service and was sent to job seekers by email.[9] In the message's introductory text, we stress a number of key points. First, we provide information about market tightness in the main occupation of interest. Specifically, we inform job seekers that the occupation in which they are currently looking for work has few vacancies available, but that many unemployed people are looking for work in that occupation. This implies poor prospects of finding employment.

[9]The design was selected based on a pilot study where job seekers indicated their preferences over multiple versions of the visualization.

Figure 2: Example of information message visualization




Second, we mention that with their skills and experience, there are alternative occupations they would qualify for (or could relatively easily qualify for) that provide much better job prospects. In this way, we try to convince job seekers of the urgency of considering alternatives, as well as reassure them that their skills and experience will fit in the new occupation.

Figure 2 shows an example of the visualization we use. We first list job seekers' primary occupation of interest, together with a bar of which the length and color (gree, yellow or red) represent the likelihood of finding a job (1). Then, we show each of the alternative occupations that we matched to the job seeker's primary occupation of interest. The order in which we show these alternative occupations is largely based on the number of historical transitions we observed and, to a lesser degree, on the job finder prospects associated with the alternative occupation. For each of the alternative occupations, we show the job finding score in the same way as for their occupation of interest (2). We also include two main skills associated with the occupation (3). While the use of historical switches between occupations ensures that all presented suggestions are relevant, individuals may have idiosyncratic skills that fit well with one occupation in

particular. We want to ensure that job seekers realize that their existing skills and experience can be valuable in another occupation. Many of the occupations with poor prospects we select are at risk of being automated. The set of alternative occupations we propose to them have better short-term job prospects. However, the longer-term prospects of these occupations vary. As job seekers may want to avoid occupations with poor long term prospects due to automation risks, we include this information in the treatment as well. If an occupation is at low risk of automation ($50^{th}$ percentile of automation risk or lower), we mention this to the job seeker (4).[10] Lastly, there is a link for more information about the occupation (extended description, required certifications, various job titles, etc.) (5).

The experiment included another treatment arm, adding to the informational message a link to a motivational video showcasing job seekers who recently made a career transition. In cooperation with a professional video maker, we compiled their stories into a motivational compilation video that addresses the main challenges, costs and benefits of occupational transitions. Since a small fraction of people clicked on the link, we merged both treatment arms for the analysis. Details on the motivation intervention are provided in the Appendix C.

## 4.3 Randomization, data collection and timeline

We selected the sample on 15 March 2021, which was composed of the stock of job seekers that were registered to search primarily for one of the 21 selection occupations. We ended up with 30,129 individuals who remained unemployed until the first message (April 12). These individuals constitute our experimental sample. Job seekers were randomly assigned to three equally sized groups: (1) the information group, (2) the information + motivation group and (3) the control group. Randomization was stratified by gender, unemployment duration and selection occupation. A random third was selected to receive pre- and post-intervention surveys (equally-sized across treatment groups).[11] After selecting the baseline sample, we administered the pre-intervention survey followed by the intervention messages and the post-intervention survey. Subsequently, we sent out 'outflow surveys' to those who found jobs. Finally, we obtain access to administrative data on employment and unemployment insurance (UI) benefits

[10] The automation risk is measured with the indicator proposed by Nedelkoska and Quintini (2018)

[11] Response was incentivized through donations to charity.

Table 1: Timeline experimental set-up and sample sizes

| Date | Event | Treatment 1 (Information) N = 10,075 | Treatment 2 (Info + video) N = 10,050 | Control N = 10,004 | Total N = 30,129 |
|---|---|---|---|---|---|
| March 23, 2021 | Pre-survey sent | 3308 | 3310 | 3292 | 9910 |
| | Respondents | 899 | 959 | 931 | 2789 |
| April 12, 2021 | First message | *Information* | *Info + video* | *No message* | |
| | | 10,075 | 10,050 | 10,004 | 30,129 |
| May 10, 2021 | Second message | | *Only video* | | |
| | | | 9022 | | |
| May 28, 2021 | Third message | *Information* | *Information* | *No message* | |
| | | 8388 | 8450 | 8399 | 25,237 |
| June 7, 2021 | Post-survey | 2766 | 2781 | 2752 | 8299 |
| | Respondents | 400 | 457 | 421 | 1278 |
| June 24, 2021 | Outflow survey 1 | 1833 | 1813 | 1799 | 5445 |
| | Respondents | 579 | 550 | 588 | 1735 |
| Sept 9, 2021 | Outflow survey 2 | 1427 | 1402 | 1411 | 4240 |
| | Respondents | 473 | 491 | 439 | 1403 |
| Dec 1, 2021 | Outflow survey 3 | 1057 | 1037 | 1004 | 3098 |
| | Respondents | 377 | 353 | 327 | 1057 |
| April 5, 2022 | Outflow survey 4 | 402 | 412 | 443 | 1257 |
| | Respondents | 106 | 107 | 136 | 349 |
| August 30, 2022 | Outflow survey 5 | 402 | 411 | 389 | 1202 |
| | Respondents | 130 | 118 | 104 | 352 |
| Jan-01-2020 until Dec-31-2023: | | | | | |
| Admin data: employment, benefits | | 10,068 | 10,041 | 9,992 | 30,101 |

Minor sample selection steps were applied prior to each intervention message: only those who (1) did not yet exit unemployment insurance, (2) had valid email addresses and (3) did not change their 'unemployment-indication' were included. Prior to the post-survey an additional subset was removed that either denied the consent statement in the pre-survey or that clicked the 'unsubscribe' button in the pre-survey. Each survey was followed by an email reminder after one week.

for the entire sample for the time period 2020 - 2023. Table 1 provides a precise timeline with corresponding sample sizes.

The pre- and post-survey contained questions about job search behavior (primary search occupations, alternative search occupation, applications and interviews), questions about beliefs (job findings prospects in the primary and alternative occupations, beliefs about wages) and various questions regarding willingness to explore and search for occupations other than the primary occupation. Further details can be found in Section 5 where we present descriptive statistics.

We sent the first intervention message on April 12, 2021. It contained the information visualization for both treatment groups and the additional video link for the motivational treatment group. In Section 6.1 we provide statistics on the engagement with the email. We find that 64% opened the email, but few clicked on the link to the video. As a result we sent an extra email with only the video link to the corresponding treatment group on May 10, 2021. Finally, a general

reminder was sent on May 28, 2021, containing the information visualization, modified based on clicking statistics from the first message.

The administrative data that we use contains employment spells, including earnings and hours, as well as benefits receipts. However, it does not contain information about the occupation. To collect information on the occupations the unemployed exit to, we therefore administered outflow surveys. Every two to three months, we selected all job seekers in our sample for whom we observed in the administrative data a labor income increase of more than €300 in the preceding months.[12] Such a substantial increase in earnings should reflect a new job. Since many job seekers hold part-time and temporary jobs during their unemployment spell, they may not have left the unemployment insurance system yet and therefore this is a preferred selection criteria. In addition, we also added everyone who left the unemployment insurance system with registered indication 'employed' to the outflow-survey sample. The outflow survey contains a number of questions about the new job (starting date, occupation, and a comparison of tasks relative to the pre-unemployment job). It is important to note that these outflow surveys are intended only for those who found a job. For that reason, we specify in the invitation that the survey is only relevant if individuals indeed found a job. Once individuals open the survey, they are asked once again if they indeed found a job and only then do they continue on to the survey.

## 4.4 Sample restrictions

For the main analyses in our paper, we impose two more sample restrictions on top of those discussed in Section 4.1. First, we restrict our main analyses to occupations with structurally poor prospects, rather than those whose poor prospects can primarily be attributed to Covid.[13] Due to the Covid pandemic, the state of the labor market fluctuated substantially around the start of our experiment, as illustrated by the fluctuations in unemployment and vacancy rates depicted in Figure B1 in the Appendix. Until early 2020, unemployment was low and stable, while it increased to 5.5% in the summer of 2020 and steadily decreased from there on. Vacancies mirror this trend. Despite our selection occupations sharing low prospects in early 2021, they differ substantially in the

[12]For example, for the first outflow survey (in June 2021) we selected recipients for whom monthly earnings in April and/or May were at least €300 higher than their highest monthly earnings in February and March.

[13]None of the Covid occupations would have been included in our experiment based on their late 2021 prospects.

longer-run trends. Most importantly, there was large variation in the degree to which occupations were affected by the various social distancing measures that were imposed to minimize the number of Covid cases. We can, in fact, identify a subset of our selection occupations that offered poor prospects primarily because of the Covid measures, but offered substantially better prospects prior to the Covid pandemic *and* after many restrictions were lifted over the summer of 2021. We classify all selection occupations as 'Covid-occupations' if the job finding score decreased with at least two points at the onset of the Covid pandemic *and* increased at least two points in the summer of 2021. Within our 21 selected occupations, there are 7 'Covid occupations' and 14 'Non-covid occupations'. In Figure B2 in the Appendix, we show how the job finding score evolves for the two groups. As expected, the Covid occupations (right panel) offer decent prospects before the pandemic and almost fully recover in late 2021. For the non-Covid occupations (left panel) this is not the case, and job prospects have been structurally poor during the past years.

That said, the impact of our treatment on those looking for work in Covid occupations is also interesting. In fact, we preregistered the split between Covid and non-Covid occupations as a heterogeneity analysis without knowing that their labor market prospects would diverge. At the time of our intervention, there was much policy interest in labor market mobility for occupations affected by Covid, and one might therefore have expected that the impacts of our treatment would be large. However, there are two reasons for why one might expect smaller treatment impacts for those looking for work in Covid occupations. First, many job seekers may have anticipated that the Covid restrictions were temporary and these individuals may therefore have been less willing to consider switching occupations. Second, even if the intervention does encourage occupational transitions, the improvement in labor market opportunities following these transitions is smaller because the low demand in those occupations was not structural.

Second, we restrict the main analysis sample to unemployed who did not work at all before the start of our experiment. The main reason for doing this is that we observe a striking difference in pre-intervention hours worked, despite the control and treatment group being balanced on demographics (indicating the randomization was successful). Figure B6 in the Appendix shows this difference. This difference in hours worked between control and treatment group prior to the intervention may create a bias in our treatment effect estimates. We address this

by restricting our sample to those individuals who do not work in March 2021 (just before our intervention starts). Within this sample all characteristics are balanced between control and treatment groups. This group in particular can be expected to benefit most from the information about potential career switches since they do not work at all. This restriction is similar to that used in Crépon et al. (2013).[14]

We do report the treatment impact on our primary outcomes of interest for individuals in Covid-occupations and those who worked a positive number of hours before the start of the experiment in Section 6.2.4. However, unless otherwise mentioned, the Figures and Tables from Section 5 onwards are based on the 'Non-covid, 0-hours worked prior to the experiment' sample.

## 4.5 Hypotheses

The aim of the intervention is to make job seekers aware of suitable alternatives to the occupations they are currently looking for work in, and motivate them to look for work in these occupations. If effective, the likely impact on job finding is not straightforward, however. In the short term, the expected effect on the likelihood of finding a job is ambiguous. On the one hand, when individuals start looking for work in more promising occupations, they will likely have more vacancies to apply to, with fewer competing job seekers per vacancy. On the other hand, despite the relevancy of the suggested alternatives, job seekers will likely have less experience in these new occupations, decreasing their comparative advantage. Moreover, they might need some time to adjust their search efforts.

Once individuals have had time to adjust, a successful intervention would likely lead to treated job seekers ending up in different occupations. Since the alternative occupations offer better job opportunities, one would expect that these job seekers will be more often employed and remain with the same employer for longer. While the differences in the demand for and supply of labor between these occupations may lead to higher wages in the alternative occupations, it is important to note that we do not take this into account in the intervention. We therefore make no predictions on changes in earnings conditional on having a job. Regardless, total earnings are likely to be different between the control and treatment groups, because of different employment rates.

[14]They "focus on results for those who did not claim to be employed at baseline" (p.550).

# 5 Descriptive results

Before turning to the analysis of the impact of the interventions in Section 6, we first provide descriptive statistics for our sample and document a range of descriptive findings regarding job search behavior and beliefs in our data.

Table 2 shows the characteristics of our sample, and how these change when we impose the sample restrictions mentioned in Section 4.4. The first column shows that our initial sample of 30,129 job seekers receiving unemployment insurance skews female and is 47 years old on average. Average unemployment duration is over 7 months, indicating that many seem to be struggling to exit unemployment, though most job seekers are still entitled to substantial benefits: 51 weeks on average. More than half of the job seekers have attained a two- to four-year vocational degree (medium education), with the rest being equally divided between those without a post-secondary education degree[15] (low education) and those who obtained a higher education degree (higher education). Perhaps most interesting is the share of job seekers that was still actively working at the time of selection into the experiment (March-2021) and the share looking for work in 'Covid' occupations, as these are what determine inclusion in the main analysis sample. The Table shows that about two-thirds of our sample did not work at all. About half of selected job seekers is looking for work in a Covid occupation.

The second column of Table 2 shows how restricting the sample to those who do not have any job in March-2021 affects the sample characteristics. There are very few changes, though a notable exception is the share of taxi drivers. A substantial share of job seekers looking for work in this occupation work more than zero hours, while collecting benefits. As providing rides has increasingly become part of the gig economy, it seems likely that these job seekers are supplementing their income this way. The third column adds the 'Non-Covid' restriction. This does affect the sample characteristics in a number of ways. First, the share of men increases, likely caused by receptionists, a female-dominated occupation, being excluded. Moreover, this sample is clearly higher educated than the overall sample, with about 31% having a higher education degree. Naturally, the opposite holds for the 'Covid' sample (Column 4).

[15]This includes individuals who graduated from a 1-year vocational education program, as these are not sufficient to obtain a 'starting qualification'.

Table 2: Descriptive statistics (administrative data): comparison of samples

| | Overall sample | 0 hours worked in Mar-2021 | | |
|---|---|---|---|---|
| | | Overall | Non-Covid | Covid |
| **Demographics:** | | | | |
| Male | 25% | 25% | 28% | 22% |
| Age | 47 (13) | 47 (13) | 48 (12) | 47 (13) |
| Unemployment duration (wks.) | 32 (28) | 30 (26) | 32 (27) | 28 (24) |
| Remaining benefits (wks.) | 51 (30) | 52 (30) | 52 (29) | 53 (31) |
| Lower education | 22% | 22% | 17% | 29% |
| Medium education | 56% | 55% | 52% | 58% |
| Higher education | 22% | 23% | 31% | 14% |
| **Experiment:** | | | | |
| Zero hours March-2024 | 68% | 100% | 100% | 100% |
| Covid selection occ. | 49% | 52% | 0% | 100% |
| Treatment | 67% | 67% | 66% | 67% |
| Pre-survey completed | 9.3% | 10.0% | 9.7% | 10% |
| **Selection occupation:** | | | | |
| Activity counsellor | 3.5% | 3.3% | 6.3% | 0% |
| Animal caretaker | 1.4% | 1.4% | 2.8% | 0% |
| Archivist | 1.0% | 1.2% | 2.3% | 0% |
| Bartender/waiter | 16% | 16% | 0% | 34% |
| Canteen/Buffet employee | 6.6% | 6.5% | 0% | 14% |
| Event/conference organizer | 2.5% | 2.6% | 5.0% | 0% |
| Graphic designer | 2.7% | 3.0% | 5.8% | 0% |
| Hairdresser | 1.9% | 1.9% | 0% | 3.9% |
| Hotel receptionist | 1.7% | 1.6% | 0% | 3.4% |
| Janitor/Concierge | 2.9% | 2.9% | 5.6% | 0% |
| Office support staff | 21% | 22% | 42% | 0% |
| Primary school teaching assistant | 2.2% | 2.1% | 4.1% | 0% |
| Printer | 1.1% | 1.2% | 2.3% | 0% |
| Producer (television/film) | 0.9% | 1.0% | 1.9% | 0% |
| Receptionist | 17% | 17% | 0% | 35% |
| Shop attendant household/leisure | 1.4% | 1.3% | 2.4% | 0% |
| Social worker | 8.0% | 8.3% | 16% | 0% |
| Steward/stewardess | 1.0% | 1.0% | 1.9% | 0% |
| Taxi driver | 4.6% | 3.1% | 0% | 6.5% |
| Travel agent | 1.6% | 1.8% | 0% | 3.7% |
| Video and sound technician | 1.0% | 1.1% | 2.1% | 0% |
| Observations | 30,129 | 20,632 | 10,738 | 9,894 |

Remaining benefits and unemployment duration are measured in March 2021.

## 5.1 How do job seekers search?

For the subsample that completed the pre-intervention survey (N = 2,789) we obtain a rich set of responses regarding job search beliefs and activities. While those invited to the survey were randomly selected, those who responded may not be. Comfortingly, in Table A6 in the Appendix we compare the survey respondents to the rest of the sample and conclude they are fairly similar. There are no significant differences in gender composition or unemployment duration.

Only the remaining benefit rights are higher for survey respondents and there is a slight difference in the distribution across selection occupations. Based on observable characteristics, we conclude that we can interpret the survey responses as fairly representative of the full experimental population.

Survey respondents first indicate what their primary search occupation is (typically the selection occupation) and which alternative occupations they consider. In Figure B3 in the Appendix we show how many occupations respondents list as their search occupations (their primary occupation, as well as alternatives). Almost 25% searches for work in only one occupation, while 40% searches in two or three occupations. Around 35% searches in more than three occupations. In Appendix Table A8, we show that most respondents (i) spend at least some hours per week exploring alternative occupations, (ii) are fairly willing to consider new occupations, (iii) have quite some confidence in their ability to work in an occupation in which they have no experience, and (iv) believe that their skills are transferable. Over 50% of respondents expects to widen their search in terms of occupations if they are still unemployed in two months.

For the primary and first alternative search occupation, we collect various measures of job search activities and elicit beliefs about the returns to job search (see Table 3). As the primary search occupation is for most individuals the selection occupation, it has a low job finding score (3.00, Row 1).[16] The first alternative occupation that they search in offers better prospects with an average job finding score of 4.29. In the previous two weeks the average number of applications for jobs in the primary occupation is 3.2, while it is 2.5 for the first alternative occupation (Row 2). The resulting number of job interviews follows a similar pattern: 0.44 for the primary occupation and 0.36 for the first alternative. The number of interviews per application is slightly higher for the alternative occupation (Row 4), which is consistent with the higher job finding score. Except for interviews, all of these differences are statistically significant.

## 5.2 How well are job seekers informed about job prospects?

We elicit a range of beliefs about the returns to job search activities and labor market prospects. The key question of interest is whether expectations regarding job prospects in various occupations align with actual prospects. In addition, we explore whether these expectations drive job search activities. First, respondents

[16]Participants can indicate at the start of the pre- and post-surveys that the selection occupation is not their primary occupation of search and provide a different primary occupation.

Table 3: Comparison primary and alternative occupation (survey data)

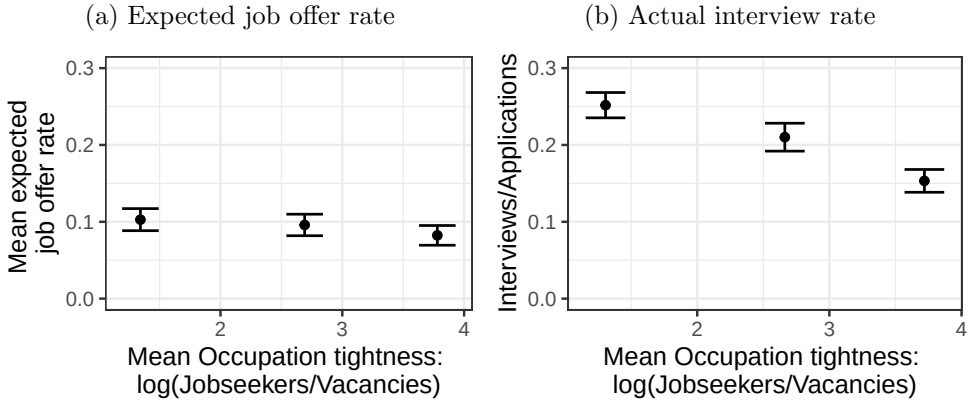
| | Primary occupation | Alternative occupation | P-value |
|---|---|---|---|
| **Job search activities:** | | | |
| Job finding score | 3.00 (0.55) | 4.29 (1.55) | <0.001 |
| Applications sent (past 2 weeks) | 3.2 (7.0) | 2.5 (4.9) | 0.009 |
| Job interviews (past 2 weeks) | 0.44 (1.55) | 0.36 (1.00) | 0.21 |
| Interviews per application | 0.15 (0.54) | 0.21 (0.50) | 0.078 |
| **Expectations:** | | | |
| Expected job offer rate | 0.09 (0.10) | 0.10 (0.11) | 0.091 |
| Expected wage (in euro) | 2,937 (893) | 2,929 (951) | 0.86 |
| Reservation wage (in euro) | 2,823 (863) | 2,801 (873) | 0.61 |
| Job stability | 0.67 (0.31) | 0.70 (0.28) | 0.013 |
| Exp. appl. if equal job offer rate | 3.92 (6.81) | 4.33 (8.60) | 0.31 |
| Exp. appl. if equal wage | 4.10 (6.93) | 4.46 (9.13) | 0.41 |
| Exp. job offer rate in 2 months | 0.08 (0.10) | 0.08 (0.10) | 0.60 |
| Observations | 1,040 | 1,040 | |

Standard deviations in brackets. Only Non-covid occupations and individuals that worked zero hours in March-2021."Primary occupation" is the occupation that the respondent searches primarily in. "Alternative occupation" is the occupation that the respondent considers the most important alternative occupation of search. The number of observations varies slightly across variables due to item non-response. "Job stability" is defined as the expected probability of being able to keep a new job for at least two years. "Exp. appl. if equal job offer rate" is the expected number of applications per week in case the job offer rate would be equal in the primary and alternative occupation. "Exp. appl. if equal wage" is the expected number of applications per week in case the job offer rate *and* the expected wage would be equal in the primary and alternative occupation. "Exp. job offer rate in 2 months" is the expected job offer rate in case the respondent is still unemployed in two months time.

indicate their belief about the number of applications it requires on average to obtain one acceptable job offer, both for their primary occupation and their first alternative. By inverting this number we obtain the expected job offer rate (per application), which is fairly small on average (0.09, Row 5 in Table 3) and strikingly similar between the primary and alternative occupation. We do not have a direct measure of the actual job offer rate, but the job finding score shows a larger difference between the primary and alternative occupation (3.00 versus 4.29, respectively). This shows that while alternative search occupations offer better prospects on average, even these alternatives are far from the best occupations (as the job finding score ranges from 2-10).

To provide further insights on how well job seekers are informed about job prospects, we link their beliefs to the actual job finding prospects. We exploit variation across individuals in their selection of alternative occupations. Specifically, we examine the relation between occupation's log-tightness (in three equally sized bins) and expected job offer rate in Figure 3. In Panel (a) we find that this relation is very flat: regardless of the true tightness, the expected job offer rate of an application is always close to 0.1. It seems that job seekers do not

Figure 3: Occupational job finding prospects for job seekers' first alternative occupation. Observations grouped into three equally sized bins.




select their alternative search occupations on the basis of better job prospects: most job seekers select alternatives with only marginally better job prospects, while, surprisingly, even those who select high-prospect alternatives do not seem to be aware of these better job finding chances.

These conclusions hinge on the question whether the occupational tightness is indeed a good measure for job prospects for job seekers who have experience in other occupations. Conditional on their background, the prospects in these alternatives might not actually be so favorable. In Panel (b) of Figure 3 we investigate whether the better job prospects translate into better returns to job search based on the reported number of applications and interviews. We see some indication that indeed the occupations with a more favorable tightness lead to a higher interview-per-application rate. We conclude that, on average, job seekers are not aware that job finding prospects are significantly better in their alternative occupations. Lastly, Table A9 shows how beliefs change over time for the control group. While job seekers become slightly more optimistic about the probability of finding a job in two months, we find no evidence that they (differentially) update their beliefs about the prospects of the primary and alternative occupation.

Returning to Table 3, we find that job seekers also have extremely similar wage expectations for the primary and alternative occupations and also hold similar reservation wages. Expectations about job stability (the probability of keeping a new job for at least two years), are slightly more optimistic for the alternative occupation with a small but significant difference. Rows 9 and 10 show how many applications job seekers think they would send *per week* to their

primary and alternative occupations if the job offer rate and the wage, respectively, are equalized. Interestingly, this number is much higher than what they do in reality and closes the gap between the primary and alternative occupation. Finally, the last row shows that job seekers expect to update their expectations about job offer rates, but only slightly. If they are still unemployed in two months time, they expect the job offer rate to be 0.08 for the primary occupation (compared to 0.09 now) and 0.08 for the alternative occupation (compared to 0.10 now).

Summing up, we draw the following two key conclusions regarding job search strategies of the job seekers in our sample.

1. While most job seekers indicate that they are willing to search in alternative occupations, and confident about doing so, the majority searches only in 1 to 3 occupations.

2. Job seekers do not appear to be informed about the the stark difference in job finding prospects between their primary search occupation and potential alternatives.

These two findings are encouraging for the potential of information interventions that bring the variation in job prospects to job seekers' attention.

# 6 Empirical analysis

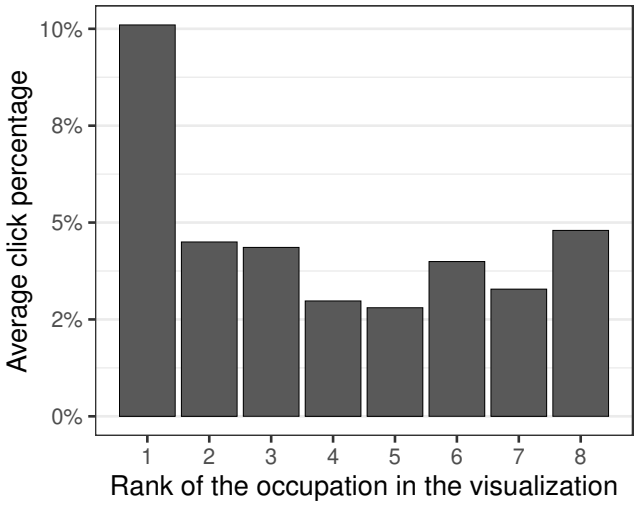
## 6.1 Take-up: opening message and clicking statistics

Job seekers in the treatment groups received their first message with occupational information on April 12, 2021 (see Section 4.3). We first compare the suggested occupations to the occupations in which job seekers report they search, to assess to what degree we provide 'new' information. Then we present statistics on engagement: whether they opened the email and clicked on the links. These statistics provide strong indication of 'treatment take-up'.

If most job seekers already search in a couple of occupations that we offer as 'high prospect alternatives', we are unlikely to provide novel information to these job seekers. In Figure B4 in the Appendix, we show the number of suggestions that an individual received in the messages that were already present in their search set as measured in the pre-intervention survey.[17] It turns out that the vast

[17]Both the search occupations and the suggestions are defined at the 5-digit BRC+ level.

Figure 4: Clicking of occupations




majority (78%) searches in none of the suggested occupations before receiving the messages. A small group was already searching in one of our suggested occupations (18%) and a negligible share was already searching for more than one suggested occupation.

A total of 19,960 job seekers received the first message (both treatment groups). From these, 12,804 opened the email (64%). Each occupation is clickable for more information about the occupation (e.g., description, tasks, skills, related occupations, educational level). The share of recipients that clicks on each occupation provides a measure of how interesting each occupation is to job seekers. In total, we observe 4,975 clicks on occupations. These are not evenly distributed across the total of 165 presented suggestions (21 selection occupations with each between 7 and 9 occupational suggestions).

In Figure 4 we show how the number of clicks depends on the ranking of the suggestions within the visualization. The occupation ranked at the top of the list is by far most popular, while also the last ones are slightly more popular. The popularity of the first suggestion reflects both (i) that job seekers start at the top of the visualization when reading the message and (ii) that suggesting that the higher placed suggestions are the most suitable ones.[18]

[18]This is because the suggestions are primarily ranked based on the number of historically observed transitions. We can disentangle the two because the ranking was not perfectly aligned with the number of transitions, and we allowed for the Public Employment Service in making choices in the order in which we present the transition occupations. A simple regression at the occupation-level (165 observations) uncovers the importance of both rank and transitions (see Table A10 in the Appendix). We find that conditional on the rank, the number of transitions, while not observable to job seekers, is highly statistically significant (Column (2)). This is

We sent a reminder email with a similar visualization on May 28th. In coordination with the communication experts from the Public Employment Service we decided to change the content slightly. Using the regression model from Column (3) of Table A10 we generated predicted interest, controlling for the rank in the first message. Thus, we predict interest based on the job finding probability, the automation risk indicator and the number of occupational transitions. Using these predictions we created a new ordering which was implemented in the second message. In addition only the new top-5 suggestions were included to make the message slightly shorter. The message was sent out to 16,838 individuals, of which 11,475 opened it (68.1%). Of those who opened it, 2,442 clicked on a link (21.3%). Over both emails, 15,867 individuals opened at least one (78.8%), of which 4,874 clicked on at least one link (30.7%).

The motivational treatment group received a version of the first message that contained an extra paragraph with a link to the motivational video. In contrast to our occupational suggestion links, very few people (0.5%) clicked on the video link. A likely explanation might be that the video was only provided *after* the information visualization, and many readers may not have reached this part of the message. Of course, it might also be that job seekers are simply not interested in the video. We sent an additional message to this treatment group that *only* provided the video link (not the occupation information). This message led to a slightly higher click rate (7.5%), but still the overall share of the motivational treatment group that has seen the video remains low. Given the low 'take-up' of the video, our analysis in the next sections combine the two treatment groups and only measure the effect of the informational content that both groups received.

## 6.2 Experimental analysis

Given the randomized assignment, the empirical strategy is straightforward and we can simply compare outcomes across the treatment and the control group.[19] Following our pre-analysis plan, we first consider the primary outcomes, which

encouraging, as it suggests that our method of selecting suitable ('fitting') occupations seems effective. In Column (3) we show that the job finding score and the indicator for the suggestion displaying 'low-automation risk' also increase the number of clicks. Again, this is encouraging, as it suggests that we are providing relevant information.

[19]Balancing checks are reported in Appendix. We obtain near-perfect balance on the stratification variables (gender, unemployment duration in three bins and selection occupation), but the samples are also balanced on all other characteristics (see Appendix Table A4 for our main analysis sample and Appendix Table A5 for the entire sample). In Table A7 in the Appendix, we show that the samples are also balanced in terms of responses to the pre-intervention survey.

are employment (earnings, hours and occupation) and benefit receipt.

### 6.2.1 Treatment effects on employment, labour earnings and benefits receipt

Employment (hours worked), labor earnings and benefits receipt are measured at a monthly basis using the administrative records provided by the Public Employment Service. The data covers all experimental participants. Many job seekers find temporary and part-time jobs while continuously receiving (fluctuating) unemployment insurance benefits. Therefore it is typically impossible to define outflow from unemployment insurance benefits at one point in time. We take hours worked as the most comprehensive measure of employment as it aggregates across potentially multiple part-time and temporary jobs. Similarly, we consider total labour earnings as the most complete measure that takes the wage level into account. For benefit dependence, we use the amount of benefits received.

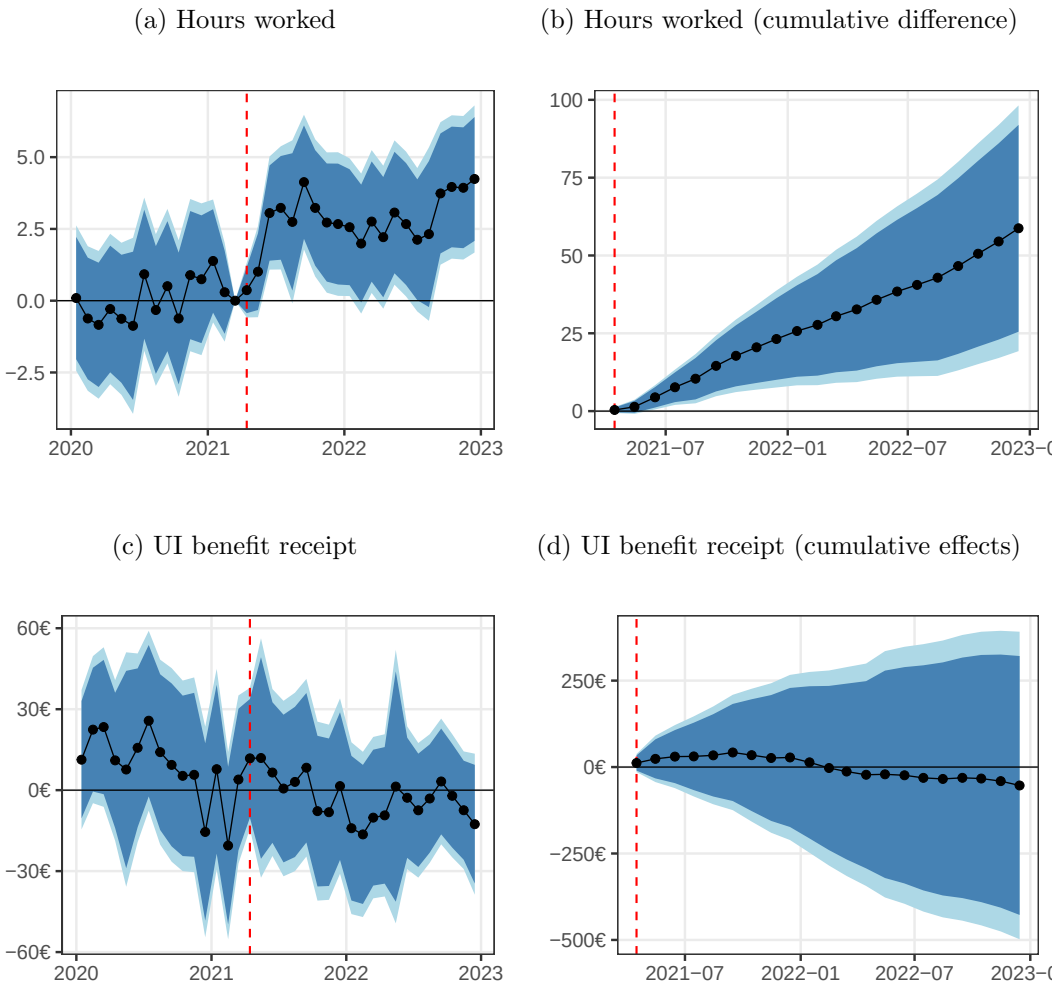
To estimate the treatment impact at various points in time, we regress the outcome measure in month $t$ on a month fixed effect ($\gamma_t$), demographic (time-invariant) controls ($X_i$) with time varying coefficients, and a treatment group dummy ($T_i$) with time varying coefficient:

$$Y_{it} = \gamma_t + X_i\beta_t + \lambda_t T_i + \varepsilon_{it} \tag{1}$$

Standard errors are clustered at the individual level and the months $t$ run from January 2020 (14 months prior to the treatment) until December 2022 (20 months after treatment). The pre-treatment months are included as an additional check of adequate randomization between treatment and control groups. Covariates $X_i$ are included to increase precision, although point estimates are hardly affected when they are excluded.

Figure 5 shows estimates of the treatment effects ($\lambda_t$) on employment, including 90 and 95% confidence intervals, for our baseline sample (job seekers in Non-covid occupations who did not work in March 2021). In Panel (a) we see that prior to the treatment there are no significant differences in monthly hours worked, with, by construction, a zero difference in March-2021. After the intervention, the treatment group always worked around 2-4 hours per month more than the control group. This difference is statistically significant in most months. Given the consistently positive coefficients, we consider the cumulative number of hours worked (starting from the treatment in April 2021) in Panel

Figure 5: Treatment impact on hours worked and benefit receipt

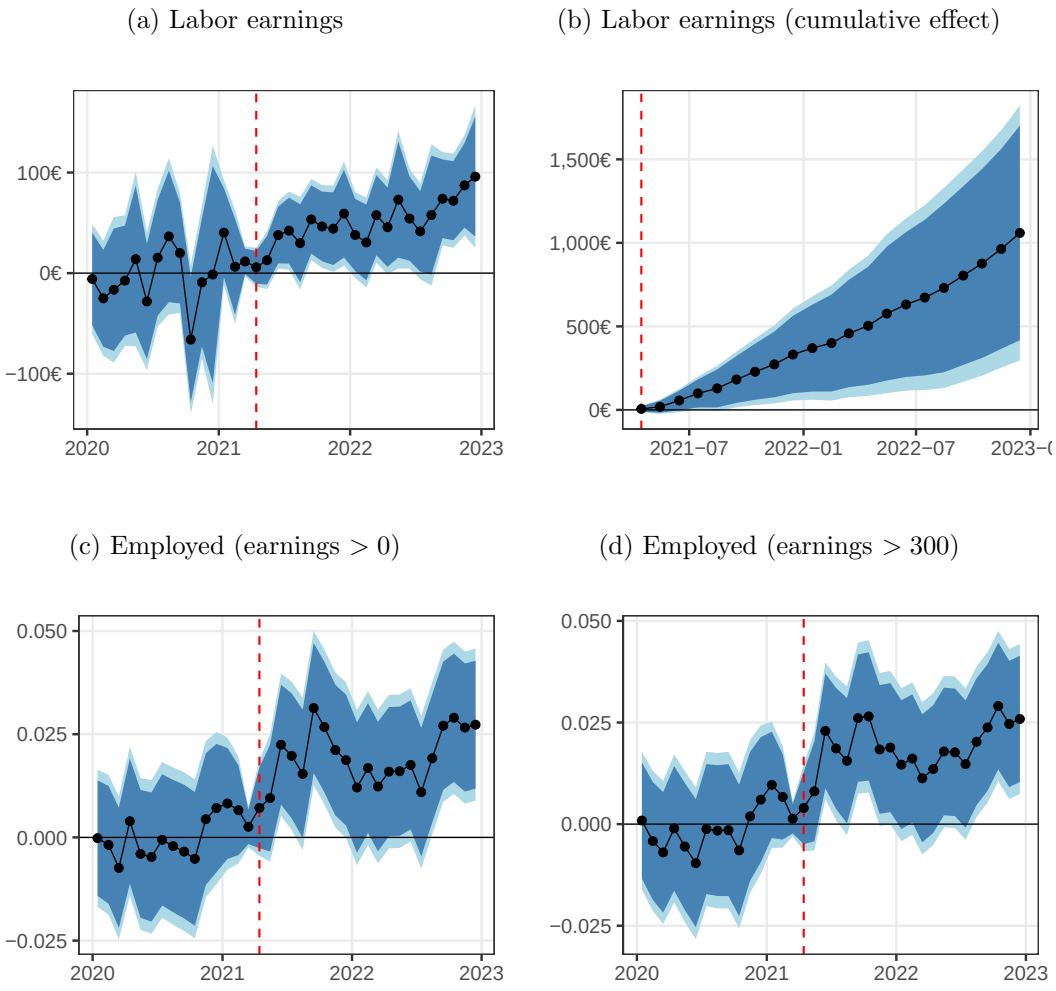



*Note:* Sample contains Non-covid occupations and individuals that worked zero hours in March-2021. The dashed red line indicates the first intervention message.

(b). We find indeed a monotone increasing difference between the control and treatment group reaching approximately 55 additional hours worked by the end of 2022. The difference is, again, statistically significant at the 5% level. We conclude that there is clear evidence that our treatment increased hours worked.

Benefit dependence is assessed in Panel (c), where the outcome is monthly UI benefit receipt (in €). We find no indication of a treatment impact, with the post-treatment coefficients close to zero and never statistically significant. The lack of results also translates into cumulative UI benefit receipt in Panel (d). There are several explanations for why the increase in hours worked is not reflected in reduced benefit receipt. First, the hours increase may simply be

Figure 6: Treatment impact on earnings and employment




*Note:* Sample contains Non-covid occupations and individuals that worked zero hours in March-2021. The dashed red line indicates the first intervention message.

too small in magnitude to induce a reduction in benefits. Second, a substantial part of the increased hours of work may have occurred for individuals who, at that time, exhausted their UI benefits. The latter is particularly relevant, since we show in Section 6.2.3 that the treatment impacts are larger among long-term unemployed who are likely to exhaust their benefits during our observation window.

In Figure 6 we consider monthly labour earnings. In Panel (a) we find no significant differences prior to the intervention, while the post-treatment coefficients are all positive, with most months showing statistical significance at the 5% level. In Panel (b) we find that the treatment impact on cumulative earnings grows

over time, again significant at the 5% level. Toward the end of 2022, the treatment impact reaches a magnitude of around € 1100. In Panel (c) we consider employment, measured by an indicator for positive labour earnings. Again we find no significant differences in any pre-treatment period, and a positive difference in all post-treatment periods (significant at the 5% level for most months). Employment is about 2 - 2.5 percentage points higher in the treatment group. These findings are corroborated by Panel (d) where we use a higher threshold for earnings to capture 'substantial' labour earnings (exceeding €300 per month). Here we also find a significant increase in employment for those that received the information messages.

The impact on employment appears of similar magnitude as the impact on hours and earnings, suggesting that (most of) the positive effects are extensive margin responses. Indeed, if we estimate our model for hours worked conditional on positive hours, or on earnings conditional on positive earnings, we find zero impact (see Appendix figures B5). While this supports the interpretation that effects work mainly on the extensive margin, it also suggests that the *additional* jobs found due to the the intervention are not of worse quality: they are associated with a similar number of working hours and similar earnings.

To provide a sense of the magnitudes, we can compare these estimates against the control-group means measured 12 months after the intervention. For monthly hours worked the control mean is 63, such that the 2.2 additional hours (Figure 5, Panel (a)) constitutes a 3.5% increase. For labor earnings the control mean is €1040 such that the approximate €45 increase (Figure 6, Panel (a)) constitutes a 4.3% increase. For employment the control mean is 54% such that the approximate increase of 1.6%-point (Figure 6, Panel (c)) constitutes a 2.9% increase. These effect sizes appear of similar magnitude and we consider them sizable given the relatively light-touch nature of the intervention and the (likely) partial take-up of the informational content.

### 6.2.2 Type of work found

Our intervention was intended to stimulate mobility towards alternative occupations. Because administrative data does not capture the occupations of jobs found, we analyze our outflow survey. As described in more detail in Section 4.3, the outflow survey was sent at three-month intervals to all experiment participants for whom administrative records reported a substantial increase in monthly earnings over the preceding months. Such an increase in earnings is a strong

Table 4: Outflow survey

| | Control | Treatment | P-value |
|---|---|---|---|
| Invited to survey | 40.4% | 42.0% | 0.10 |
| Opened survey | 13.2% | 14.8% | 0.019 |
| Responded job found | 11.7% | 13.1% | 0.030 |
| Observations | 3,611 | 7,127 | |

Sample contains Non-covid occupations and individuals that worked zero hours in March-2021. Figures are aggregates across all outflow survey waves (see Table 1 for details).

proxy of job finding.[20] As a result, the survey provides occupational information for individuals who (i) for the first time post-treatment experienced a substantial labor earnings increase and (ii) confirmed in the survey that they started a new job and completed the survey questions.

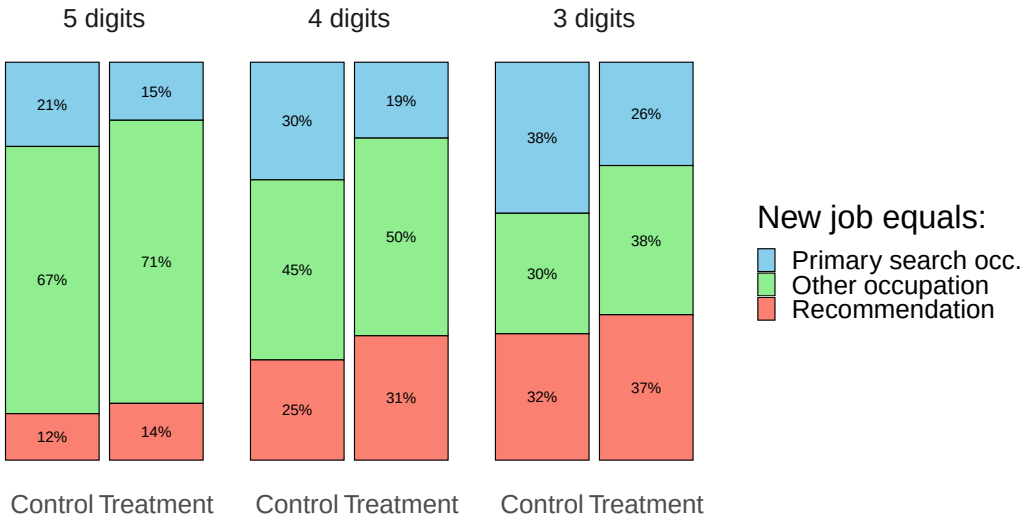
Table 4 provides a summary of the response to the survey. Of the 10,738 individuals in our non-Covid subsample, 4,452 (41%) received an invitation to fill out the outflow survey. The first row shows that the share of treated individuals who received an invitation is slightly higher (42.0%) than that of the control group (40.4%). While this is consistent with our results based on administrative data from the previous section, the difference is not statistically significant. The share opening the survey is significantly higher in the treatment group. This is noteworthy, as the invitation explicitly mentioned that the survey was intended for people who had found a job. In the last row we show that 11.7% of the control group individuals confirmed in the survey that they started a new job, while this is slightly larger for the treatment group (13.1%). The latter might create selection bias in the responses to which we return below (but note that the difference is small, limiting the magnitude of potential selection bias).

Figure 7 provides information on the types of jobs found. The figure shows whether the occupation in which a job was found was the same as their primary search occupation, equal to one of our recommended alternatives, or an entirely different occupation. We show these results at three levels of granularity: 5-digit (the most detailed level and the level at which selection took place), 4-digit, and 3-digit.[21]

[20]Practical challenges in terms of data access made it impossible to use actual data on job finding on a rolling basis for selecting survey recipients.

[21]The survey asked for a free text job title, which were blindly coded into a 5-digit occupational code. It is possible that a 4-digit or 3-digit occupation contains both the 5-digit primary occupation and a 5-digit recommended occupation. In these cases, we consider whether for that individual, the new job equalled the primary occupation or a recommendation at the more

Figure 7: Comparison of occupations of new jobs with the primary search occupations and the set of recommendations (at different occupational digit levels)




*Note:* Sample contains Non-covid occupations and individuals that worked zero hours in March-2021. 'Primary search occ' reports the share of individuals who found work in the same occupation as their initial 'primary occupation of search' (registered at time of registration for UI benefits). 'Recommendation' reports the share of individuals who found work in one of the occupations recommended to them, *excluding* the primary search occupation (especially at higher occupational coding levels these two often overlap). The p-values for equal shares of Primary search occupations are 0.02 (5 digit), 0.001 (4 digit) and 0.0005 (3 digit). The p-values for equal shares of Recommendation Occupations are 0.28 (5 digit), 0.06 (4 digit) and 0.16 (3 digit).

At the 5-digit level, we find that 21% of control group individuals find a job in their primary search occupation. In the treatment group, this number is only 15%; a difference of 6 percentage points ($p$-value for equal shares = 0.02). At this fine-granular level, we are likely to also capture switches to occupations that are very much interconnected. Occupational changes at a higher level of aggregation are likely to reflect more substantial changes of occupations. At the 4-digit and 3-digit level, we find that difference between treatment an control groups increases to 11 and 12 percentage points (both strongly statistically significant). At the 4-digit level, the treated group is 6 percentage points more likely to find a job in a recommended occupation, though this difference is only weakly significant (p-value = 0.06). Also at the 3-digit level this difference persists, although not statistically significant (p-value = 0.16). Note that classification errors would

granular (more digits) level and use that to classify the job at the less granular (fewer digits) level.

lead us to underestimate the shares in the figure for primary occupations (in blue) and recommendations (in red). Since the classification was performed blindly with respect to the treatment status, there is, however, no reason to believe that this affects the difference between treatment and control group.

As shown in Table 4, the response rate to the outflow survey was slightly higher in the treatment group (13.1/42.0 = 31.2%) than in the control group (11.7/40.4 = 29.0%). However, it is straightforward to show that potential selectivity in the response rate cannot explain the occupational differences.[22]

In summary, we find evidence that employment (hours worked and earnings) increased in the treatment group, while UI benefit receipt did not change. In addition, new jobs were found in more diverse occupations in the treatment group.

### 6.2.3 Heterogeneity by unemployment duration

Our sample size allows investigating which groups of individuals were particularly receptive for the intervention. We pre-registered two dimensions of heterogeneity to avoid data mining. These dimensions are based on previous studies that found stronger impacts among (1) long-term unemployed and (2) job seekers that search 'narrowly' (Belot et al., 2019, 2022). Unfortunately, our search breadth measures are not sufficiently detailed to classify job seekers, and we focus solely on unemployment duration. We split the sample at the median UI duration in our sample (measured at the time of sample selection), which is 24 weeks. Results are presented in Figure 8, where we focus on hours worked and employment for brevity. We find clear heterogeneity. The impact on hours worked is large and statistically significant for long-term unemployed in Panel (a), while it is positive but smaller and statistically insignificant for the short-term unemployed in Panel (b). For employment (measured as positive labor earnings) we find a similar difference: large and significant impacts for long-term unemployed (Panel c) and positive but insignificant estimates for the short-term unemployed (Panel d).

[22] If the response rate in the treatment group had been equal to that of the control group, the number of respondents would have been reduced by 67. In the extreme case, all of these additional respondents had reported an occupation different from their primary search occupation. Under that assumption, the true statistic for the share of new jobs equal to the primary search occupation in the treatment group (blue area in Figure 7, 5-digit panel) would have been 15.7% instead of the observed value of 14.6% (note that the figure reports 15% due to rounding). Indeed, even in this extreme scenario the number is substantially smaller than in the control group (21%).

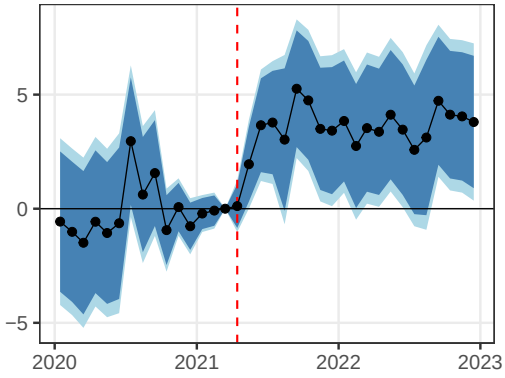
These compelling results raise the question whether it is the longer unemployment duration perse that drives the responsiveness to information about alternative occupations, or whether dynamic selection alters the composition of the sample relative to short-term unemployed. In Table A11 in the Appendix we compare the characteristics of the two groups. We find that long-term unemployed are significantly older and slightly lower educated, two differences that one might have associated with lower willingness to explore a career switch. Other differences exist, but are fairly minor (e.g., gender and occupational shares). While only suggestive, these results support the idea that it is indeed the extended duration that causes treatment impacts to be larger, most likely because it boosts the willingness and incentives to explore alternative occupations. Indeed, if we compare responses to the pre-intervention survey among short- and long-term unemployed, we find that beliefs about job findings are significantly more pessimistic among the long-term unemployed (see Table A12 in the Appendix).

#### 6.2.4 Treatment effects on job seekers in 'Covid' occupations and with paid employment at the time of intervention

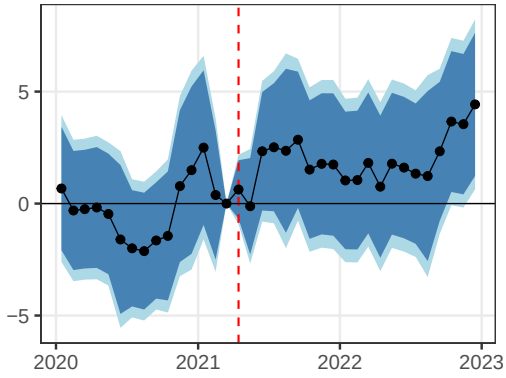
While we consider the findings reported in Section 6.2.1 to be our main results, it is worthwhile to investigate how the treatment affected job seekers looking for work in the 'Covid occupations' (i.e., occupations that quickly recovered after the Covid-19 pandemic) and registered job seekers with a paid job at the time of the intervention. Table 5 shows the treatment effect on a range of outcomes measured 18 months after the intervention. For comparison, the first row shows the impact of the treatment on our main sample, reproducing the positive and significant impact on hours worked and earnings. The second row considers individuals in Covid-occupations, where we find smaller and insignificant effects. The point estimates for the cumulative impacts on hours and earnings are about half of those in Non-covid occupations. The lack of impact for this group can be explained in one of two ways. First, job seekers in these occupations may have benefited less from our advice, as their occupations recovered in subsequent months. That is, the impact of heeding our advice is smaller. A second explanation is that individuals in these groups were less likely to take our advice, as they saw demand in their occupations return to their pre-Covid levels. Figure B7 in the Appendix shows that the latter explanation is more likely. While Figure 7 shows that treated individuals in Non-covid occupations find jobs in different occupations than those in the control group, Figure 7 shows that this is not the

Figure 8: Heterogeneous treatment impact by unemployment duration

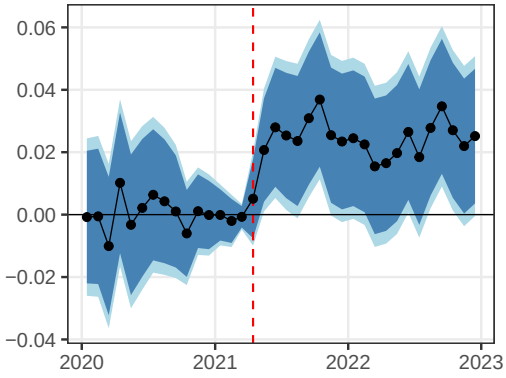
(a) Hours worked: long duration



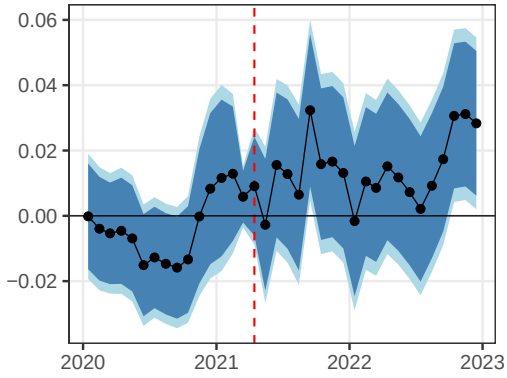

(b) Hours worked: short duration




(c) Employed (earnings $> 0$): long duration




(d) Employed (earnings $> 0$): short duration




*Note:* Individuals in Non-covid occupations without employment in March-2021. Long unemployment duration is defined as longer or equal than 24 weeks at the time of sample selection. Short unemployment duration means shorter than 24 weeks. The dashed red line indicates the first intervention message.

case for the Covid sample. Note that despite Covid occupations reverting to their baseline levels, job prospects in the suggested occupations were still significantly better, even after Covid restrictions were lifted in the Netherlands. Individuals therefore may still have benefited from switching occupations.

The last row of results shows the impact for those who already held a paid job while receiving unemployment insurance at the time of our intervention. Here, we find no effects and estimates that are comparatively much closer to zero. We conclude that job seekers who were already employed were much less likely to integrate the advice into their job search.

Table 5: Treatment effects on other samples: Covid occupations and job seekers with partial employment

| | *Dependent variable:* | | | | | | |
|---|---|---|---|---|---|---|---|
| | Monthly hours worked | Monthly labour earnings | Monthly UI benefits received | Labour earnings above 0 | Cumulative hours | Cumulative earnings | Cumulative UI benefits |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Zero employment in March-2021, non-covid occupations (baseline sample) | | | | | | | |
| Treatment | 3.96*** | 71.97*** | −2.10 | 0.03*** | 50.56*** | 876.21** | −33.22 |
| | (1.27) | (24.02) | (11.59) | (0.01) | (18.17) | (347.86) | (216.11) |
| Observations | 10,738 | 10,738 | 10,738 | 10,738 | 10,738 | 10,738 | 10,738 |
| Covid-occupations (non-employed in March-2021) | | | | | | | |
| Treatment | 1.00 | 14.26 | 0.25 | −0.003 | 24.59 | 349.98 | −28.66 |
| | (1.29) | (20.39) | (8.48) | (0.01) | (18.83) | (283.08) | (166.76) |
| Observations | 9,894 | 9,894 | 9,894 | 9,894 | 9,894 | 9,894 | 9,894 |
| Positive employment in March-2021, non-covid occupations | | | | | | | |
| Treatment | −0.24 | 9.24 | 11.21 | −0.003 | −0.14 | −221.34 | 353.64 |
| | (1.63) | (32.67) | (11.67) | (0.01) | (24.48) | (514.42) | (220.74) |
| Observations | 4,563 | 4,563 | 4,563 | 4,563 | 4,563 | 4,563 | 4,563 |

Each cell contains a treatment effect estimate from a regression that controls for demographics. All outcomes are measured 18 months after the intervention (October 2022). Robust standard errors in parentheses.

### 6.2.5 Treatment effects on measures of job search

The positive impacts on employment and the corresponding increase in occupational mobility suggest that job seekers have adopted our advice in their job search strategies. We obtained two sources of information regarding individual job search activities to test whether this is the case.

First, we investigate the job search activities that are registered through the official Public Employment Service platform. Job seekers face a requirement to complete at least four activities every four weeks. These activities can consist of job applications or other search activities such as network meetings and open inquiries with employers. The activities are registered online by the job seekers or by the case worker if a meeting took place. We observe all activities registered between March 2021 and April 2022. The advantage of this measure is that it encompasses search through all possible channels (different online job boards, direct applications, applications through social networks). In addition, the search requirement (with potential sanctions in case of failure to meet the minimum) improves the reporting rate. The weakness is, however, that job seekers may face limited incentives to report anything beyond their required number of activities. In addition, the data contain only the activity and date, without any information about the job that was considered. Therefore, we simply re-estimate equation

1, using the number of activities registered per month as the outcome.[23] We present the estimates in Panel (a) of Figure B8 in the Appendix. We find some indication that the number of applications increased after our intervention: the difference between control and treatment group is close to zero before the first message was sent, and turns positive (and statistically significant in most months until early 2022) after our intervention. The increase is about 0.1 applications, relative to a control mean of 1.8 in March 2021.

Our second source of information about job search are online search activities on the Public Employment Service job search platform. This platform is one of the largest in the Netherlands and is generally recommended to UI beneficiaries for their job search. We observe all job search activities (vacancies viewed, saved and applied to) for individuals in our sample that use the platform while being logged in, between March-June 2021. The advantage of these data is that they contain more details about the vacancies (occupation). The disadvantage is that it is not mandatory for job seekers to use the platform, and as a result only a small (and selective) share does. In an attempt to obtain insights from the data, we first restrict our analysis to all individuals who used the platform at least once before our intervention. This avoids diluting the sample with many individuals who never use the platform. Second, we only consider viewed vacancies, as observation numbers for saved and applied vacancies are very low. Again we re-estimate equation 1, using the number of viewed vacancies per month as the outcome. The results in Panel (b) of Figure B8 in the Appendix show that there is no indication of a treatment effect. The number of viewed vacancies is slightly larger for the treatment group, but the difference already exists before the treatment and is only marginally significant.

We conclude that there is some evidence that the intervention has boosted job search. Unfortunately, data limitations prevent a more detailed investigation of how job search was exactly affected.

### 6.2.6 Treatment effects on survey responses

We now turn to secondary outcomes of interest, which are survey measures of job search behavior and beliefs about the labor market. These are measured through the post-intervention survey and therefore only available for the small

[23] One complication is dynamic selection: once job seekers find a job, they stop registering job search activities. To deal with this, we remove individuals from the sample once they work at least 40 hours within one month.

Table 6: Difference-in-differences analysis survey outcomes: Job search activities

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Time exploring | Applications | Interviews | Number of search occupations | Mean jobfinding score | Suggestions used in search set |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatment | 0.006 | 0.382 | 0.582 | −0.004 | −0.029 | 0.048 |
| | (0.595) | (1.672) | (0.438) | (0.147) | (0.110) | (0.052) |
| Post | −0.956 | 1.024 | 0.067 | −0.257 | 0.207* | 0.053 |
| | (0.682) | (1.927) | (0.510) | (0.168) | (0.126) | (0.060) |
| Treatment*Post | −0.354 | −1.783 | −0.088 | −0.073 | −0.164 | −0.058 |
| | (0.841) | (2.364) | (0.619) | (0.208) | (0.156) | (0.074) |
| Constant | 5.801*** | 6.738*** | 0.533 | 2.662*** | 3.806*** | 0.183*** |
| | (0.482) | (1.362) | (0.361) | (0.119) | (0.089) | (0.042) |
| Mean Dep. Var. | 5.21 | 6.91 | 0.93 | 2.51 | 3.84 | 0.22 |
| Observations | 792 | 250 | 280 | 792 | 746 | 746 |

*p<0.1; **p<0.05; ***p<0.01. Individuals in Non-covid occupations without employment in March-2021. The dependent variables are: weekly time spent on exploring alternative occupations (Column 1), total number of weekly applications (Column 2), total number of weekly interviews (Column 3), number of occupations included in the search, (Column 4), the mean job finding score of the set of search occupations (Column 5) and the number of suggestions from the message that are included in the set of search occupations (Column 6).

subset of participants who completed the survey.

For the outcome variables that we collected through the survey, we have precise pre-intervention measurements and we opt for a difference-in-differences model that controls for baseline differences to increase statistical power. The baseline specification is

$$Y_{it} = \beta_0 + \beta_1 T_i + \beta_2 P_{it} + \beta_3 P_{it} T_i + \varepsilon_{it}, \tag{2}$$

with $T_i$ a treatment indicator and $P_i$ a time period indicator (equal to 1 for the post-intervention period, and 0 otherwise). Using the survey data, we first consider measurements of job search activities and beliefs. In Table 6 we show regression estimates. The number of observations varies across columns, as we only include individuals who answered the respective questions in both the pre- and post-intervention surveys. We consider the following outcomes: (1) weekly time spent on exploring alternative occupations, (2) total number of weekly applications, (3) total number of weekly interviews, (4) number of occupations included in the search, (5) the mean job finding score of the set of search occupations and (6) the number of suggestions from the message that are included in the set of search occupations. We find that the treatment effect estimate ($\beta_3$), is never statistically significantly different from zero. Thus we cannot reject that the treatment has no observable impact on job search activities as measured along these six dimensions.

Table 7: Difference-in-differences analysis survey outcomes: labor market beliefs

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Job offer rate per application primary | Job offer rate per application alternative | Expected stability primary | Expected stability alternative | Job finding probability |
| | (1) | (2) | (3) | (4) | (5) |
| Treatment | −0.008 | 0.030 | −0.012 | 0.040 | 0.068* |
| | (0.059) | (0.089) | (0.034) | (0.039) | (0.038) |
| Post | 0.122* | 0.085 | −0.010 | −0.004 | 0.092** |
| | (0.070) | (0.108) | (0.039) | (0.045) | (0.043) |
| Treatment*Post | −0.048 | −0.086 | 0.003 | 0.020 | −0.017 |
| | (0.084) | (0.126) | (0.048) | (0.055) | (0.053) |
| Constant | 0.101** | 0.162** | 0.657*** | 0.660*** | 0.258*** |
| | (0.050) | (0.076) | (0.027) | (0.032) | (0.031) |
| Mean Dep. Var. | 0.14 | 0.2 | 0.64 | 0.69 | 0.34 |
| Observations | 356 | 212 | 792 | 498 | 570 |

*p<0.1; **p<0.05; ***p<0.01. Individuals in non-Covid occupations without employment in March-2021. The dependent variables are: weekly time spent on exploring alternative occupations (Column 1), total number of weekly applications (Column 2), total number of weekly interviews (Column 3), the mean job finding score of the set of search occupations (Column 4) and the number of suggestions from the message that are included in the set of search occupations (Column 5).

Next, we perform a similar analysis for the beliefs. We consider: (1) the expected job offer rate per application in the primary occupation (Column 1) and (2) first alternative occupation (Column 2), the expected job stability of a job in the primary occupation (Column 3) and the alternative occupation (Column 4) and the probability of finding employment in the next two months (Column 5). Again, we find no statistically significant effects of the treatment on any of the belief measures.

These results are difficult to square with our finding that treated job seekers more often find employment in occupations different from their initial occupation of interest. However, there are a number of possible explanations for the lack of impact that we find on search behavior and beliefs. First, sample size becomes fairly small at this stage, with only around 300-600 observations for some outcomes (implying 150-300 individuals per treatment/control). Starting from an experimental sample of 10,738, this limits statistical precision. Indeed, wide confidence intervals cannot reject substantial positive (or negative) impacts. Second, the small sample size also hints at the possibility of selective response: while those invited to answer the survey were randomly drawn, those who completed both the pre- and post-survey are certainly not representative of the full sample. Third, search activities and beliefs may be difficult concepts to measure in a survey, resulting in measurement error (in both the pre- and post-survey)

and attenuation bias in our estimates.

# 7 Conclusion

What does it take to stimulate job seekers to broaden their horizon and look for jobs with better prospects? To answer this question we provide unemployed job seekers looking for work in occupations with poor labor market prospects with personalized information about a manageable number of suitable alternative occupations that offer better prospects.

A first key insight is that job seekers searching within occupations with poor labor market prospects are not averse to considering alternatives. On the contrary, they are open to exploring other occupations and confident in their ability to secure employment in these occupations. However, they appear unaware of why such a shift might be necessary or beneficial. This stems from limited knowledge of how unfavorable the prospects are in their primary occupation, as well as a lack of awareness of the better prospects in the alternatives they do consider.

Given this starting point, it is perhaps unsurprising that our intervention has an effect on employment outcomes such as employment probability, hours worked, and earnings. The intervention delivered digestible and personalized information about the poor prospects in the occupations job seekers were currently targeting. Importantly, it also offered concrete and attainable alternative occupations, presented in a user-friendly format with practical guidance on how to transition into them. We find that unemployed job seekers whom we informed more often switch away from their primary search occupations, more often find employment in the occupations we suggest to them, but also in other occupations than those we suggest to them. This evidence suggests that the information that we shared has landed, and that unemployed job seekers in occupations with poor prospects indeed broaden their search for a more successful outcome.

Interestingly, we find that our main findings primarily hold for unemployed job seekers in 'Non-covid occupations', i.e., occupations with a structural low demand for labor. For job seekers in 'Covid occupations', i.e., occupations for which the demand was low at the time of our experiment due to Covid-related restrictions, and unemployed with a paid job, we find smaller and insignificant effects. This is likely due to the fact that the information we designed is less relevant to these groups.

From a policy perspective, the integrated design of our intervention, both

in terms of individualizing publicly available information and in terms of the carefully designed message directed to job seekers in occupations that are in low demand provide relevant and immediately applicable insights. In many countries information on recent trajectories of job seekers is available, which can be used to generate suitable occupational suggestions. As it is low-cost and easy to implement, this intervention highlights a promising avenue for Public Employment Services in helping job seekers in slack labor markets.

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# Appendix A: Additional Tables

Table A1: Selection occupations with low job prospects

| Occupation | Occupation (Dutch name) |
|---|---|
| Activity counsellor | Activiteitenbegeleider |
| Animal caretaker | Dierenverzorger |
| Archivist | Archiefmedewerker |
| Bartender/waiter | Medewerker bediening/bar |
| Canteen/Buffet employee | Medewerker bedrijfsrestaurant of buffet |
| Event/conference organizer | Organisator van conferenties en/of evenementen |
| Graphic designer | Grafisch vormgever |
| Hairdresser | Kapper |
| Hotel receptionist | Hotelreceptionist |
| Janitor/Concierge | Conciërge/huismeester |
| Office support staff | Ondersteunend medewerker op een kantoor/secretariaat |
| Primary school teaching assistant | Onderwijsassistent basisonderwijs |
| Printer | Drukkerijmedewerker |
| Producer (television/film) | Productieleider/producent |
| Receptionist | Receptionist/telefonist |
| Shop attendant household/leisure goods | Verkoopmedewerker huishoudelijke en vrijetijdsartikelen |
| Social worker | Sociaal werker |
| Steward/stewardess | Steward/stewardess |
| Taxi driver | Taxi- of particulier chauffeur |
| Travel agent | Reisadviseur/reisbureaumedewerker |
| Video and sound technician | Beeld- en geluidtechnicus |

Table A2: Sample comparison for occupation of interest

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Age | Medium Education | Higher Education | Search Radius | Share Male |
| | (1) | (2) | (3) | (4) | (5) |
| Other | 2.453*** | −0.037* | 0.049 | 8.551*** | 0.205*** |
| | (0.532) | (0.020) | (0.030) | (1.753) | (0.029) |
| Transition | 2.999*** | 0.020 | −0.046 | 0.216 | 0.200*** |
| | (0.634) | (0.023) | (0.036) | (2.088) | (0.035) |
| Constant | 44.716*** | 0.335*** | 0.376*** | 36.245*** | 0.416*** |
| | (0.513) | (0.019) | (0.029) | (1.691) | (0.028) |
| Observations | 1,882 | 1,882 | 1,882 | 1,882 | 1,882 |

*p<0.1; **p<0.05; ***p<0.01

Table A3: Sample comparison for experience occupation

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Age | Medium Education | Higher Education | Search Radius | Share Male | Years of Experience |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Other | 1.925*** | −0.025 | 0.023 | 7.320*** | 0.188*** | 0.408* |
| | (0.433) | (0.018) | (0.028) | (1.349) | (0.026) | (0.214) |
| Transition | 1.755*** | 0.032 | −0.069** | 0.571 | 0.167*** | 0.157 |
| | (0.515) | (0.021) | (0.033) | (1.605) | (0.031) | (0.255) |
| Constant | 46.537*** | 0.339*** | 0.414*** | 37.376*** | 0.437*** | 5.075*** |
| | (0.419) | (0.017) | (0.027) | (1.306) | (0.025) | (0.208) |
| Observations | 2,413 | 2,413 | 2,413 | 2,413 | 2,413 | 2,413 |

*p<0.1; **p<0.05; ***p<0.01

Table A4: Balance table main analysis sample (zero hours worked in March 2021 and Non-covid occupations only): administrative records

| | Overall | Control | Treatment | P-value |
|---|---|---|---|---|
| **Demographics:** | | | | |
| Male | 28% | 28% | 28% | 0.66 |
| Age | 48 (12) | 48 (12) | 48 (12) | 0.81 |
| Unemployment duration (wks.) | 32 (27) | 32 (27) | 32 (28) | 0.98 |
| Remaining benefits (wks.) | 52 (29) | 52 (29) | 52 (29) | 0.78 |
| Lower education | 17% | 18% | 16% | 0.050 |
| Medium education | 52% | 51% | 53% | 0.24 |
| Higher education | 31% | 31% | 31% | 0.74 |
| **Experiment:** | | | | |
| Pre-survey completed | 9.7% | 9.7% | 9.7% | 0.88 |
| **Selection occupation:** | | | | |
| Activity counsellor | 6.3% | 6.5% | 6.2% | 0.56 |
| Animal caretaker | 2.8% | 2.8% | 2.8% | 0.89 |
| Archivist | 2.3% | 2.2% | 2.3% | 0.81 |
| Event/conference organizer | 5.0% | 5.3% | 4.9% | 0.34 |
| Graphic designer | 5.8% | 6.0% | 5.7% | 0.50 |
| Janitor/Concierge | 5.6% | 5.7% | 5.6% | 0.85 |
| Office support staff | 42% | 41% | 42% | 0.82 |
| Primary school teaching assistant | 4.1% | 3.8% | 4.2% | 0.39 |
| Printer | 2.3% | 2.4% | 2.3% | 0.94 |
| Producer (television/film) | 1.9% | 1.8% | 1.9% | 0.69 |
| Shop attendant household/leisure | 2.4% | 2.5% | 2.4% | 0.84 |
| Social worker | 16% | 16% | 16% | 0.98 |
| Steward/stewardess | 1.9% | 1.6% | 2.1% | 0.089 |
| Video and sound technician | 2.1% | 2.0% | 2.1% | 0.85 |
| Observations | 10,738 | 3,611 | 7,127 | |

P-values refer to tests for equality of the control and treatment columns. Remaining benefits and unemployment duration are measured in March 2021.

Table A5: Balance table overall sample: administrative records

| | Overall | Control | Treatment | P-value |
|---|---|---|---|---|
| **Demographics:** | | | | |
| Male | 25% | 25% | 25% | 0.99 |
| Age | 47 (13) | 47 (13) | 47 (13) | 0.47 |
| Unemployment duration (wks.) | 32 (28) | 32 (28) | 32 (28) | 0.68 |
| Remaining benefits (wks.) | 51 (30) | 51 (30) | 51 (30) | 0.81 |
| Lower education | 22% | 22% | 21% | 0.17 |
| Medium education | 56% | 55% | 56% | 0.13 |
| Higher education | 22% | 23% | 22% | 0.66 |
| **Experiment:** | | | | |
| Zero hours March-2024 | 68% | 69% | 68% | 0.25 |
| Covid selection occ. | 49% | 49% | 49% | 0.77 |
| **Selection occupation:** | | | | |
| Pre-survey completed | 9.3% | 9.3% | 9.2% | 0.83 |
| Activity counsellor | 3.5% | 3.4% | 3.5% | 0.77 |
| Animal caretaker | 1.4% | 1.4% | 1.4% | 0.96 |
| Archivist | 1.0% | 1.1% | 1.0% | 0.71 |
| Bartender/waiter | 16% | 16% | 16% | 0.96 |
| Canteen/Buffet employee | 6.6% | 6.6% | 6.6% | >0.99 |
| Event/conference organizer | 2.5% | 2.5% | 2.4% | 0.88 |
| Graphic designer | 2.7% | 2.8% | 2.7% | 0.72 |
| Hairdresser | 1.9% | 1.8% | 2.0% | 0.35 |
| Hotel receptionist | 1.7% | 1.7% | 1.7% | >0.99 |
| Janitor/Concierge | 2.9% | 2.8% | 2.9% | 0.74 |
| Office support staff | 21% | 21% | 21% | 0.89 |
| Primary school teaching assistant | 2.2% | 2.2% | 2.3% | 0.55 |
| Printer | 1.1% | 1.1% | 1.1% | 0.96 |
| Producer (television/film) | 0.9% | 0.9% | 0.9% | 0.86 |
| Receptionist | 17% | 17% | 17% | 0.69 |
| Shop attendant household/leisure | 1.4% | 1.4% | 1.4% | 0.85 |
| Social worker | 8.0% | 8.1% | 8.0% | 0.97 |
| Steward/stewardess | 1.0% | 1.0% | 1.0% | 0.84 |
| Taxi driver | 4.6% | 4.7% | 4.5% | 0.45 |
| Travel agent | 1.6% | 1.5% | 1.6% | 0.64 |
| Video and sound technician | 1.0% | 1.0% | 0.9% | 0.80 |
| Observations | 30,129 | 10,004 | 20,125 | |

P-values refer to tests for equality of the control and treatment columns. Remaining benefits and unemployment duration are measured in March 2021.

Table A6: Comparison of composition of survey-respondents

| | Overall | Survey completed | Survey not completed | P-value |
|---|---|---|---|---|
| **Demographics:** | | | | |
| Male | 28% | 29% | 28% | 0.83 |
| Age | 48 (12) | 53 (11) | 47 (12) | <0.001 |
| Unemployment duration (wks.) | 32 (27) | 32 (29) | 32 (27) | 0.91 |
| Remaining benefits (wks.) | 52 (29) | 62 (29) | 51 (29) | <0.001 |
| Lower education | 17% | 18% | 17% | 0.20 |
| Medium education | 52% | 53% | 52% | 0.79 |
| Higher education | 31% | 29% | 31% | 0.17 |
| **Experiment:** | | | | |
| Treatment | 66% | 66% | 66% | 0.88 |
| **Selection occupation:** | | | | |
| Activity counsellor | 6.3% | 7.2% | 6.2% | 0.25 |
| Animal caretaker | 2.8% | 1.9% | 2.9% | 0.042 |
| Archivist | 2.3% | 1.7% | 2.3% | 0.17 |
| Event/conference organizer | 5.0% | 4.0% | 5.1% | 0.092 |
| Graphic designer | 5.8% | 5.6% | 5.8% | 0.72 |
| Janitor/Concierge | 5.6% | 7.5% | 5.4% | 0.016 |
| Office support staff | 42% | 46% | 41% | 0.002 |
| Primary school teaching assistant | 4.1% | 3.1% | 4.2% | 0.053 |
| Printer | 2.3% | 2.2% | 2.4% | 0.77 |
| Producer (television/film) | 1.9% | 1.6% | 1.9% | 0.53 |
| Shop attendant household/leisure | 2.4% | 2.6% | 2.4% | 0.71 |
| Social worker | 16% | 14% | 16% | 0.13 |
| Steward/stewardess | 1.9% | 1.1% | 2.0% | 0.007 |
| Video and sound technician | 2.1% | 1.0% | 2.2% | <0.001 |
| Observations | 10,738 | 1,040 | 9,698 | |

Only Non-covid occupations and individuals that worked zero hours in March-2021. P-values refer to tests for equality of the survey and non-survey columns.

Table A7: Balance table: survey responses (prior to intervention)

| | Overall | Control | Treatment | P-value |
|---|---|---|---|---|
| Job finding score sel. occ. | 3.00 (0.55) | 3.03 (0.59) | 2.99 (0.53) | 0.22 |
| Job finding score alternative occ. | 4.29 (1.55) | 4.27 (1.59) | 4.30 (1.53) | 0.71 |
| Time exploring alternatives | 6.0 (6.1) | 6.0 (6.2) | 6.0 (6.1) | 0.96 |
| Willingness work in new occ. | 3.39 (0.88) | 3.38 (0.87) | 3.39 (0.88) | 0.82 |
| **Beliefs:** | | | | |
| My skills are transferable | 3.82 (0.82) | 3.84 (0.83) | 3.81 (0.82) | 0.58 |
| Prob. job in 2 months | 0.36 (0.28) | 0.36 (0.30) | 0.37 (0.27) | 0.89 |
| Appl. needed (primary) | 48 (58) | 55 (63) | 44 (55) | 0.028 |
| Appl. needed (alt.) | 45 (57) | 52 (64) | 41 (53) | 0.065 |
| **Wage (expectations):** | | | | |
| Salary previous job | 3,016 (1,187) | 3,003 (1,220) | 3,022 (1,170) | 0.81 |
| Hours previous job | 30 (8) | 30 (8) | 30 (8) | >0.99 |
| Expected wage (main occ.) | 2,937 (893) | 2,936 (880) | 2,938 (900) | 0.98 |
| Reservation wage (main occ.) | 2,823 (863) | 2,808 (863) | 2,830 (864) | 0.70 |
| Expected wage (alt. occ.) | 2,929 (951) | 2,912 (921) | 2,938 (966) | 0.71 |
| Reservation wage (alt. occ.) | 2,801 (873) | 2,751 (848) | 2,827 (885) | 0.25 |
| **Applications/interviews** | | | | |
| Applications (main occ.) | 3.2 (7.0) | 3.5 (8.4) | 3.1 (6.2) | 0.48 |
| Job interviews (main occ.) | 0.44 (1.55) | 0.37 (1.12) | 0.47 (1.73) | 0.29 |
| Applications (alt. occ.) | 2.45 (4.91) | 2.86 (6.52) | 2.24 (3.79) | 0.17 |
| Job interviews (alt. occ.) | 0.36 (1.00) | 0.33 (1.00) | 0.37 (1.00) | 0.63 |
| Applications (other occ.) | 2.4 (4.9) | 2.4 (5.4) | 2.4 (4.7) | 0.93 |
| Job interviews (other occ.) | 0.36 (1.18) | 0.36 (1.24) | 0.36 (1.15) | 0.97 |
| Observations | 1,040 | 352 | 688 | |

Only Non-covid occupations and individuals that worked zero hours in March-2021. P-values refer to tests for equality of the control and treatment columns.

Table A8: Survey responses about broader job search

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Search occupations suggested | 1,030 | 0.23 | 0.50 | 0 | 3 |
| Weekly hours exploring alternatives | 1,040 | 6.02 | 6.10 | 0.50 | 20.00 |
| Willingness to consider other occupations (1-5) | 1,040 | 3.39 | 0.88 | 1 | 5 |
| Confidence in working without experience (1-5) | 1,040 | 3.77 | 0.82 | 1 | 5 |
| Believes that skills are transferable (1-5) | 1,040 | 3.82 | 0.82 | 1 | 5 |
| Probability to expand search in two months | 1,040 | 0.54 | 0.28 | 0.00 | 1.00 |

Sample contains Non-covid occupations and individuals that worked zero hours in March-2021. 'Search occupations suggested' measures the number of occupations that a job seeker searches in that coincide with one of the suggested occupations in our treatment messages. The variables with a 1-5 scale were answered using Likert scales (1 = Strongly disagree, ..., 5 = Strongly agree).

Table A9: How do beliefs change over time? A comparison of of survey responses (control group only).

| | Pre | Post | P-value |
|---|---|---|---|
| Prob. job in 2 months | 0.27 (0.25) | 0.36 (0.32) | 0.025 |
| Appl. needed (primary) | 69 (66) | 56 (67) | 0.24 |
| Appl. needed (alt.) | 60 (66) | 49 (61) | 0.33 |
| Reservation wage (main occ.) | 2,798 (862) | 2,774 (811) | 0.82 |
| Reservation wage (alt. occ.) | 2,715 (843) | 2,815 (999) | 0.46 |
| Appl. needed (primary) in 2 months | 64 (62) | | |
| Appl. needed (alt.) in 2 months | 61 (63) | | |
| Observations | 136 | 136 | |

Sample contains Non-covid occupations and individuals that worked zero hours in March-2021. 'Pre' refers to the pre-experiment survey and 'Post' refers to the post-experiment survey. Individuals are only included if they responded to both surveys. Standard deviations in parentheses.

Table A10: Clicking of occupations

| | *Dependent variable:* | | |
|---|---|---|---|
| | Percentage of recipients that clicks | | |
| | (1) | (2) | (3) |
| Rank 2 | $-0.06^{***}$ | $-0.05^{***}$ | $-0.05^{***}$ |
| | (0.01) | (0.01) | (0.01) |
| Rank 3 | $-0.06^{***}$ | $-0.04^{***}$ | $-0.05^{***}$ |
| | (0.01) | (0.01) | (0.01) |
| Rank 4 | $-0.07^{***}$ | $-0.05^{***}$ | $-0.05^{***}$ |
| | (0.01) | (0.01) | (0.01) |
| Rank 5 | $-0.07^{***}$ | $-0.06^{***}$ | $-0.06^{***}$ |
| | (0.01) | (0.01) | (0.01) |
| Rank 6 | $-0.06^{***}$ | $-0.05^{***}$ | $-0.05^{***}$ |
| | (0.01) | (0.01) | (0.01) |
| Rank 7 | $-0.07^{***}$ | $-0.05^{***}$ | $-0.05^{***}$ |
| | (0.01) | (0.01) | (0.01) |
| Rank 8 | $-0.05^{***}$ | $-0.04^{***}$ | $-0.04^{***}$ |
| | (0.01) | (0.01) | (0.01) |
| Jobfinding prob. (tightness) | | | $0.01^{***}$ |
| | | | (0.003) |
| Low Automation-risk | | | $0.03^{***}$ |
| | | | (0.01) |
| Relative nr of transitions | | $0.09^{***}$ | $0.09^{***}$ |
| | | (0.02) | (0.02) |
| Constant | $0.10^{***}$ | $0.08^{***}$ | 0.01 |
| | (0.01) | (0.01) | (0.02) |
| Observations | 165 | 165 | 165 |
| $R^2$ | 0.27 | 0.33 | 0.45 |

Note: This table displays OLS regression estimates at the recommendation-email level. The omitted baseline category is rank 1. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Table A11: Comparison of characteristics short and long UI duration samples: administrative records

| | UI duration < 24 wks. | UI duration >= 24 wks. | P-value |
|---|---|---|---|
| **Demographics:** | | | |
| Male | 27% | 29% | 0.062 |
| Age | 44 (13) | 51 (10) | <0.001 |
| Unemployment duration (wks.) | 11 (6) | 52 (25) | <0.001 |
| Remaining benefits (wks.) | 62 (32) | 43 (23) | <0.001 |
| Lower education | 16% | 18% | 0.004 |
| Medium education | 54% | 51% | 0.011 |
| Higher education | 31% | 31% | 0.66 |
| **Experiment:** | | | |
| Treatment | 67% | 66% | 0.59 |
| Pre-survey completed | 9.7% | 9.6% | 0.85 |
| **Selection occupation:** | | | |
| Activity counsellor | 6.3% | 6.4% | 0.72 |
| Animal caretaker | 3.5% | 2.1% | <0.001 |
| Archivist | 1.8% | 2.6% | 0.005 |
| Event/conference organizer | 5.7% | 4.4% | 0.001 |
| Graphic designer | 6.8% | 5.0% | <0.001 |
| Janitor/Concierge | 5.1% | 6.1% | 0.029 |
| Office support staff | 39% | 43% | <0.001 |
| Primary school teaching assistant | 4.2% | 4.0% | 0.63 |
| Printer | 2.2% | 2.5% | 0.29 |
| Producer (television/film) | 2.4% | 1.4% | <0.001 |
| Shop attendant household/leisure | 2.8% | 2.1% | 0.021 |
| Social worker | 15% | 17% | 0.016 |
| Steward/stewardess | 2.7% | 1.2% | <0.001 |
| Video and sound technician | 2.1% | 2.0% | 0.95 |
| Observations | 5,100 | 5,635 | |

Sample contains Non-covid occupations and individuals that worked zero hours in March-2021. P-values refer to tests for equality of the control and treatment columns. Remaining benefits and unemployment duration are measured in March 2021.

Table A12: Comparison of characteristics short and long UI duration samples: survey responses

| | UI duration < 24 wks. | UI duration >= 24 wks. | P-value |
|---|---|---|---|
| Job finding score sel. occ. | 2.97 (0.57) | 3.03 (0.53) | 0.083 |
| Job finding score alternative occ. | 4.30 (1.57) | 4.28 (1.54) | 0.83 |
| Time exploring alternatives | 6.2 (6.2) | 5.8 (6.0) | 0.25 |
| Willingness work in new occ. | 3.44 (0.85) | 3.35 (0.90) | 0.10 |
| **Beliefs:** | | | |
| My skills are transferable | 3.87 (0.82) | 3.77 (0.82) | 0.056 |
| Prob. job in 2 months | 0.42 (0.28) | 0.31 (0.27) | <0.001 |
| Appl. needed (primary) | 37 (49) | 58 (64) | <0.001 |
| Appl. needed (alt.) | 35 (49) | 55 (63) | <0.001 |
| **Wage (expectations):** | | | |
| Salary previous job | 3,015 (1,125) | 3,016 (1,242) | >0.99 |
| Hours previous job | 30 (8) | 29 (8) | 0.043 |
| Expected wage (main occ.) | 2,944 (849) | 2,931 (933) | 0.81 |
| Reservation wage (main occ.) | 2,818 (825) | 2,827 (898) | 0.87 |
| Expected wage (alt. occ.) | 2,960 (933) | 2,899 (967) | 0.37 |
| Reservation wage (alt. occ.) | 2,831 (873) | 2,772 (873) | 0.35 |
| **Applications/interviews** | | | |
| Applications (main occ.) | 3.2 (6.8) | 3.2 (7.2) | 0.95 |
| Job interviews (main occ.) | 0.45 (1.62) | 0.42 (1.47) | 0.76 |
| Applications (alt. occ.) | 2.27 (4.58) | 2.64 (5.21) | 0.31 |
| Job interviews (alt. occ.) | 0.33 (0.89) | 0.39 (1.10) | 0.40 |
| Applications (other occ.) | 2.3 (5.1) | 2.5 (4.8) | 0.60 |
| Job interviews (other occ.) | 0.42 (1.18) | 0.31 (1.18) | 0.24 |
| Observations | 497 | 543 | |

Sample contains Non-covid occupations and individuals that worked zero hours in March-2021. P-values refer to tests for equality of the control and treatment columns. Remaining benefits and unemployment duration are measured in March 2021.

# Appendix B: Additional Figures

Figure B1: Unemployment and vacancies in the Netherlands

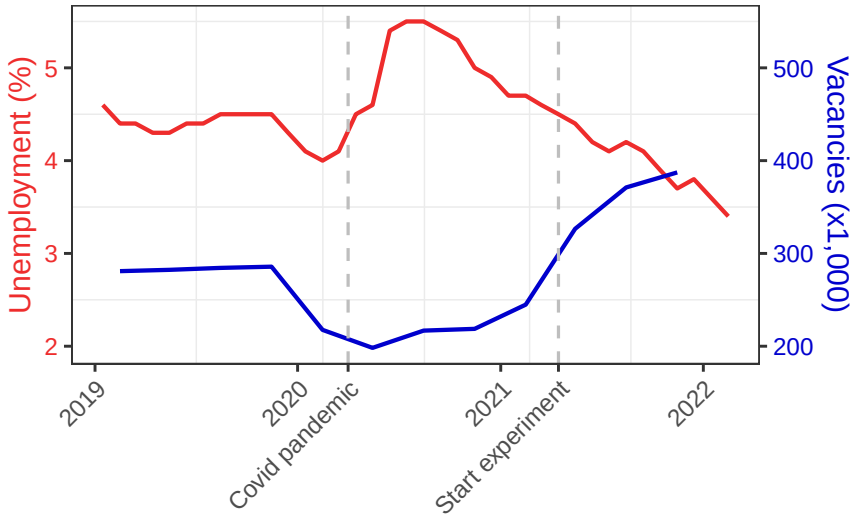



Figure B2: Job prospects of Covid and Non-covid occupations

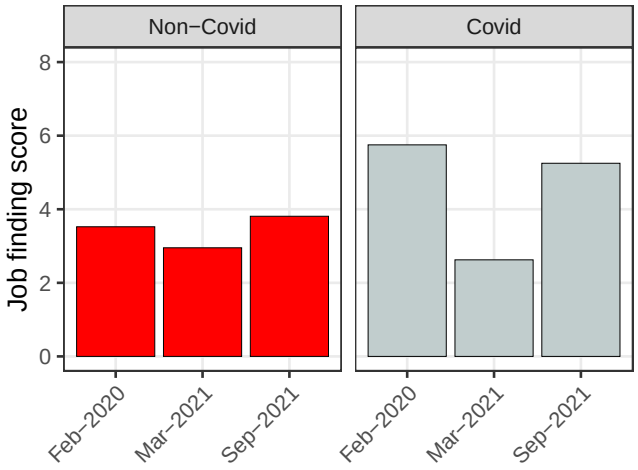


Figure B3: Number of search occupations

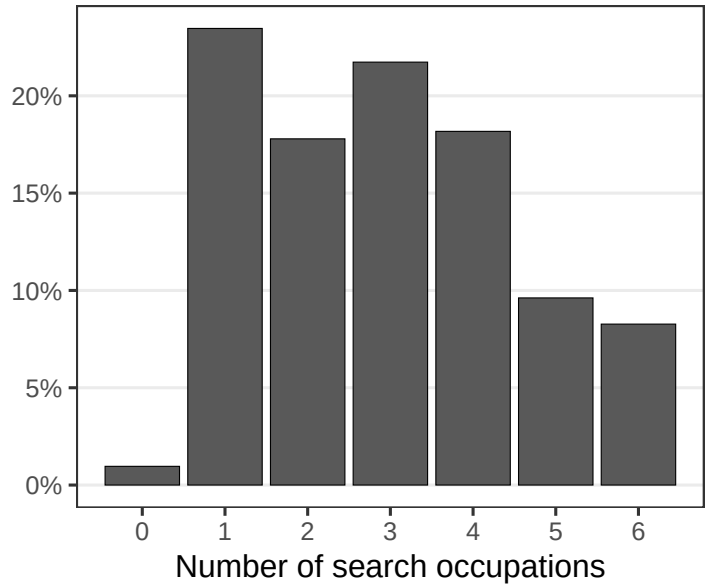



Figure B4: The number of suggested search occupations (form our intervention) that were already part of job seekers' initial set of search occupations

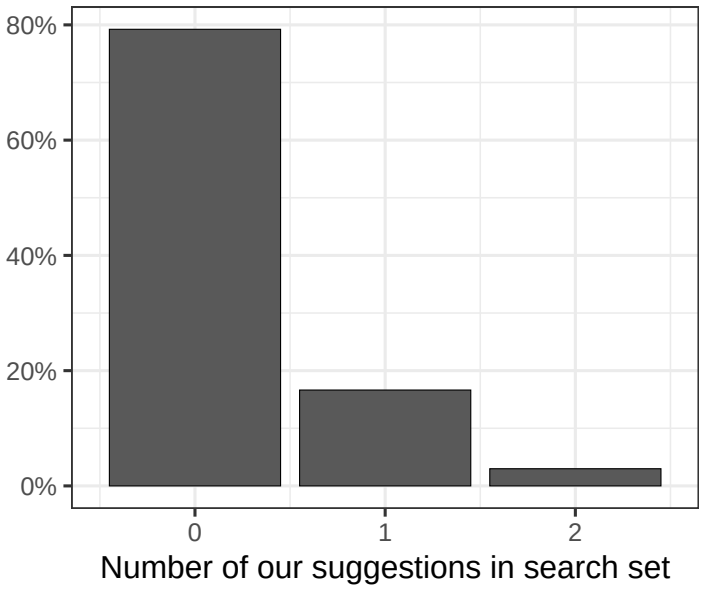
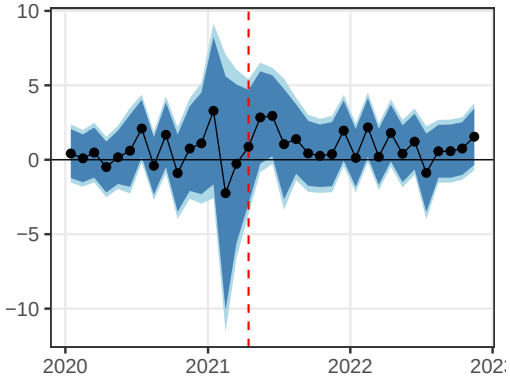
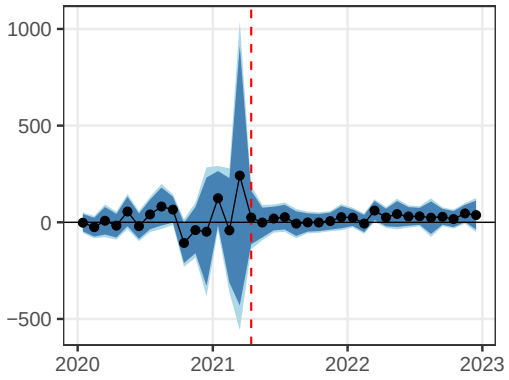


Figure B5: Intensive margin effects: treatment impacts conditional on employment

(a) Hours worked, conditional



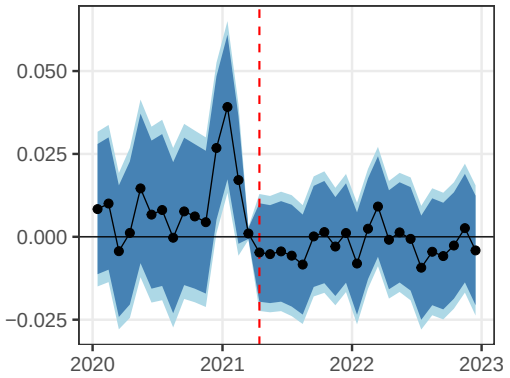

(b) Labor earnings, conditional



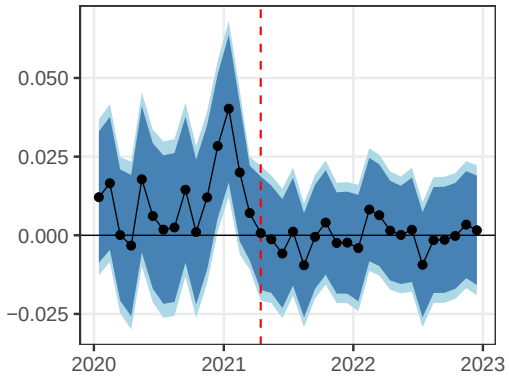

*Note:* The left panel considers only observations where the individual has positive working hours. The right panel considers only observations where the individual has positive labor earnings. Individuals in Non-covid occupations without employment in March-2021. The dashed red line indicates the first intervention message. The large confidence intervals closely before the intervention are due to our sample selection which includes only individuals without employment at that time.

Figure B6: Hours worked by month for job seekers working positive hours before treatment

(a) Employment (hours > 0)

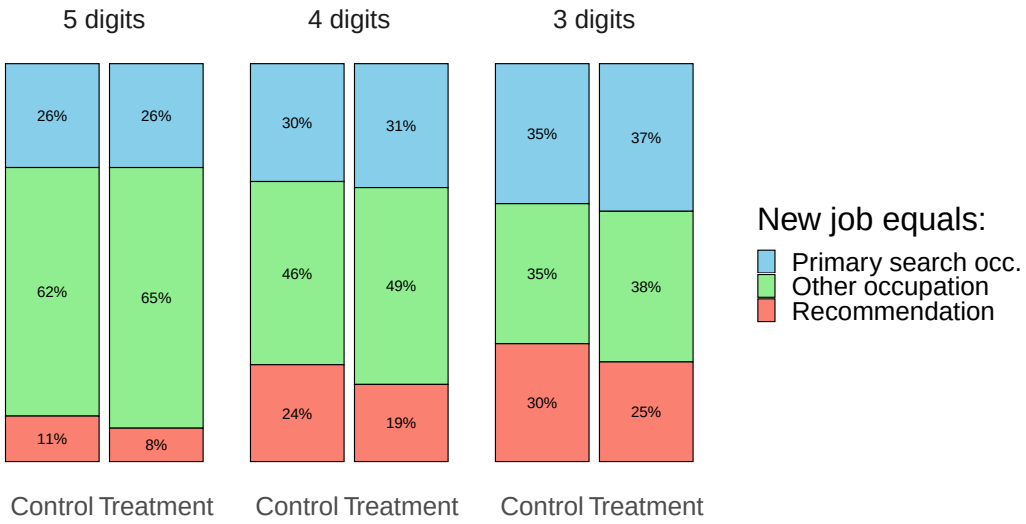



(b) Employment (hours > 300)




*Note:* Individuals in Non-covid occupations with employment in March 2021. The dashed red line indicates the first intervention message.

Figure B7: Comparison of occupations of new jobs with the primary search occupations and the set of recommendations (at different occupational digit levels): only individuals from Covid occupations.

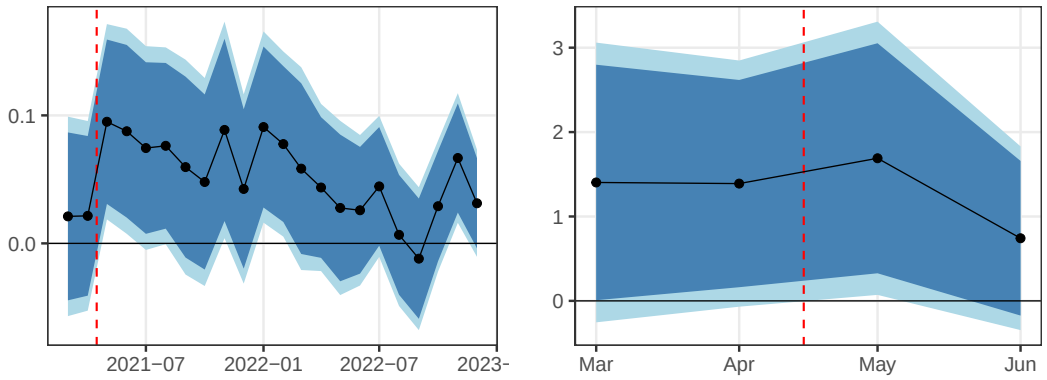



*Note:* 'Primary search occ' report the share of individuals who found work in the same occupation as their initial 'primary occupation of search' (registered at time of registration for UI benefits). 'Recommendation' reports the share of individuals who found work in one of the occupations recommended to them, *excluding* the primary search occupation (especially at higher occupational coding levels these two often overlap).

Figure B8: Treatment impact on monthly job search: registered activities and online viewed vacancies

(a) Registered activities

(b) Online search: viewed vacancies




*Note:* Individuals in Non-covid occupations without employment in March 2021. The dashed red line indicates the first intervention message.

# Appendix C: Motivational Intervention

The experiment included a second treatment arm, where a link to a motivational video was included. The intervention targeted psychological barriers to consider an occupational transition. A professional short film video was assembled, with former job seekers sharing their personal transition success stories. The aim of this video was to provide job seekers with more relatable stories about motivational challenges associated with occupational transitions and how to overcome them. While job seekers might find our alternative occupational suggestions interesting, they may still wonder if they would really be able to make the switch. Listening to the personal stories of others who have experienced such occupational transitions may be a source of motivation, as evidenced by the role models literature discussed in the introduction. We recruited role models through a newspaper column. In this column, we explained that a lot of people find occupational transitions to be difficult and perhaps even scary, and that individuals considering such a transition may benefit from learning about the experience of others. We asked individuals to submit a short, personal video. We selected nine recordings and asked a professional video maker to compile these clips into a 5-minute video. The video covers three main topics. First, the individuals introduce themselves and describe the transition they made (occupation they had before and new occupation). Second, they talk about how they experienced the transition. Third, they provide general advice and encouragement.