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

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Abstract

We study the impact of online information provision to job seekers who are looking for work in occupations with poor labor market prospects. Job seekers received suggestions about suitable alternative occupations online, and how the prospects of these alternatives compare to the job seekers' current occupation of interest. Some additionally receive a link to a motivational video for parts of the treatment group. 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. There is little impact on job seekers in "Covid" occupations which did well prior to and after the lockdowns.

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 also 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 search occupations are in low demand.

In this paper, we evaluate a low-cost 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 conduct the intervention in collaboration with the Public Employment Office in the Netherlands (UWV). The experiment involves 30,129 unemployed job seekers who recently became unemployed and search in one of 21 occupations with poor employment prospects. In a jointly designed intervention, the UWV informed 20,125 of these job seekers of 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. In the intervention, 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. The occupational suggestions are based on the most common occupational transitions observed from (i) millions of resumes from former job seekers and (ii) a longitudinal survey that is representative of the Dutch labor force. This ensures that the occupational suggestions we make are realistic switches for the targeted job seekers. From

[1]For the Covid-Pandemic, see ,e.g., del Rio-Chanona et al. (2020); Forsythe et al. (2020); for technological development and automtomation see, e.g., autor2003skill, autor2015there, brynjolfsson2018can, frey2017future.

these common and attainable transitions, we include those that currently offer sufficiently good job finding prospects.

In the second treatment, we add a motivational component to our intervention. We sourced videos from a diverse group of individuals who made a successful transition from one occupation to another. 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. Half of the email recipients in the information treatment also received a link to the motivational video in the email.

We measure the impact of the interventions on job finding probability, labour earnings, hours worked, and benefits received using administrative data.[2] On top of that, 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 we gathered shows that job seekers are, on average, willing to look for alternative occupations and are confident that they will be able to do well in these 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 also hardly correlated with true job finding prospects. These findings point towards fertile grounds for our information intervention. We do not force unemployed job seekers to broaden their job search, but do make suggestions of suitable switches with better prospects to them. Forcing a broader job search could reduce job finding rates (van der Klaauw and Vethaak, 2022).

Take-up of the information is high: we find that more than 60% 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 was rarely watched, so this treatment group is effectively also only exposed to the information part of the treatment.

The effects of the information are large for unemployed job seekers in structurally pool labor markets: Employment increased 5%, hours worked 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

[2]Further administrative data (either from online search records, or from caseworkers records) on job search activities is expected to become available for analysis in the near future.

earnings. Unemployment benefits are not cut one-for-one with income in the Netherlands to provide incentives to take low-paying or low-hour jobs, and reductions in the receipt of unemployment benefits are smaller and insignificant. In our own survey employed workers in the treatment group indeed 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.

We do not see significant effects of our intervention in "Covid" occupations which had poor labor market prospects early in 2021 but had good labor market prospects both prior to Covid (in February 2020) and after the initial waves and associated lockdowns were over (September 2021). Workers in these occupations might rationally expect the short duration of the Covid depression and chose to wait out the difficulty for a few more months rather than taking advice on alternative occupational employment.

Overall, providing targeted information had positive effects on those workers most in need of alternative suggestions due to the structural difficulties in their occupation. Given the easy and low-cost nature of the intervention this highlights a promising avenue to help job seekers slack labor markets.

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. The study builds on previous work by Belot et al. (2019) who design and test a recommendation system aimed a broadening the set of occupations considered. The experiment was conducted on a small sample (300) of UK job seekers, they included tailored occupational recommendations in an online job search platform and observed job seekers' search behavior over the course of 3 months. They find that personalized suggestions of alternative occupations affects job search and increases the chances of getting an interview.

The current study is of a much larger scale, focuses on job seekers searching in occupations with poor prospects, and evaluates the effects on finding employment (including the types of occupations). The intervention differs in that it provides information via e-mail and is not embedded in a job search platform. 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. Here the idea is to induce a change in the general 'job search strategy'.

Our work is most closely related to Belot et al. (2022) and Altmann et al. (2022) who also evaluate recommendation systems aimed at broadening job

search. Belot et al. (2022) focuses on a sample of long-term job seekers. The recommendations are 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). 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. Their 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 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 that are particularly tight to start with though. In contrast, our intervention reallocates workers from slack markets to much tighter markets. In such setting, congestion effects are likely to be much smaller.

Our study also relates to recent related 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 site of the Swedish Public Employment Service, where half of 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.

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.

From a policy perspective, getting unemployed job seekers back into employment is an important objective and the specific task of public employment agencies. For job seekers transitioning from occupations with poor labor market prospects, finding work can be particularly challenging, as it may require them to consider alternative occupations for which prospects and the match with own skills are not easy to identify. Our study contributes to this policy challenge as we evaluate the extent to which broadening the search behavior, while making use of publicly available information that we individualize to make it relevant to each individual job seekers, can help them out of unemployment.

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

2 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 Agency'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

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

register with the Dutch Public Employment Agency in order get access to unemployment benefits. 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 Agency. Based on the information entered in the 'work folder', the Public Employment Agency 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 Agency 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 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 employment office assesses occupation-specific job prospects that they publish online.[4] The Public Employment Agency also publishes a list the alternative occupations, i.e., occupational switches that jobseekers 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.[5]. 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 web-

[4]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

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

sites 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.

3 Experimental Design

3.1 Selection of occupations

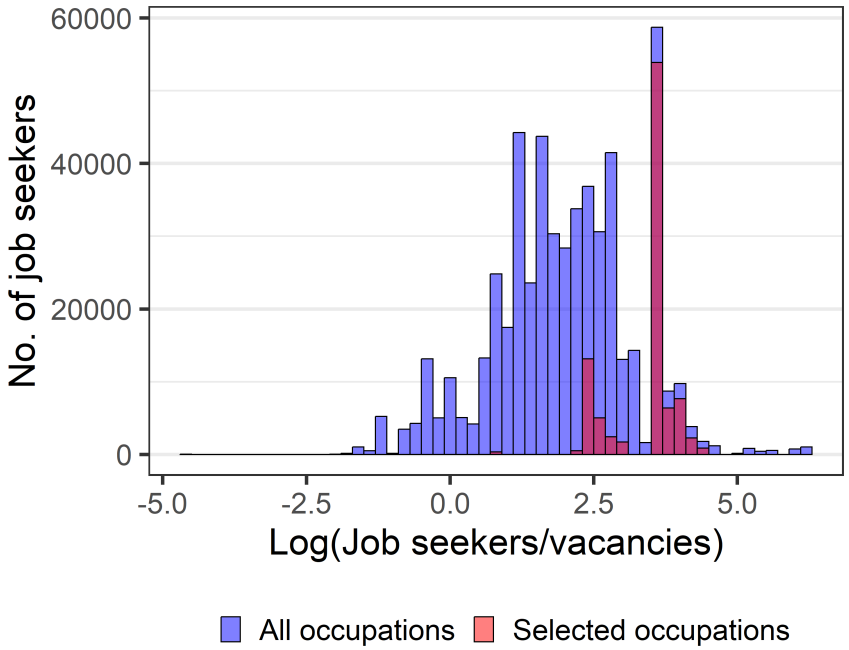
The aim of our experiment is to help unemployed job seekers who search in occupations with low employment prospects to consider different, more promising, occupations. Job seekers who search in these occupations are most likely to benefit from information on alternative occupations with better prospects.

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).[6] The score runs from 2 (very poor job prospects) to 10 (excellent job prospects). For the experiment, we selected all individuals interested in occupations (i.e., they indicated on the platform to be searching for jobs in these occupations) with a score of 2, 3 or 4 in the spring of 2021, leading to 21 '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 3 (including their relative share within the sample). Appendix Table A1 provides the original occupation names in Dutch. Figure 1 shows the distribution of market tightness (the log of job seekers/vacancies) for the primary search occupation of all unemployed job seekers.[7] The job seekers from the 21 selected occupations are highlighted in red, demonstrating that we selected occupations with the highest job seeker to

[6]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.

[7]source: UWV Open Match Data (hfttps://data.overheid.nl/en/dataset/uwv-open-match-data)

Figure 1: Labour market tightness of selected and other occupations



vacancy ratios.[8]

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 intervention email.

One potential concern is that job seekers looking for work in our selection occupations differ from those looking for work in transition occupations in ways that make them less attractive on the labor market. We use the 'Open Match

[8]Note that in the Netherlands the regional variation in labor market tightness is relatively low (https://www.werk.nl/arbeidsmarktinformatie/dashboards/spanningsindicator), hence we do not differentiate occupations across regions. The selection procedure involved consultation with labor market experts of the employment office, leading to the omission of some occupations with a very small number of job seekers, and combining some occupations that were very similar to each other.

Table 1: 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

Data' published on April 13, 2021 by the Dutch employment office to speak to this concern. 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. We link the data for each occupation to our set of selection occupations (i.e., occupations in decline, from which we sampled job seekers for our experiment), transition occupations (i.e., occupations we advised job seekers to go into), and all other occupations. There is an important caveats to keep in mind: job seekers can register interest and experience in multiple occupations. This may inflate the number of job seekers registered in the open data, as well as attenuate estimates if job seekers tend to register in different occupations types (selection, transition, and other occupations).

Table 1 shows how job seekers looking for work in our selection occupations differ from those looking for work in the transition occupations we selected, and all other occupations. There are a number of striking patterns. Educational attainment does not differ between job seekers interested in the different types 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 interested in our selection occupations have an equally sized search radius as 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 are younger on average, and less likely to be male.

Table A2 in the Appendix shows how characteristics differ between job seekers with experience in the various occupations. The results are qualitatively similar to those in Table 1. However, Table A2 additionally shows that there is no difference in experience between the selection occupations and transition occupations, despite the age difference; another positive signal for the likely 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.

3.2 Interventions

The goal of our intervention is 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 determine these suitable alternative occupations based on two metrics. First, we use historical occupational switches based on resume data that the employment office 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 sample most often switch to. We are agnostic about how these transitions have occurred, but the fact that they do occur does means it is easy enough to move from one occupation to the other. However, there are two caveats.

First, 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 Office. Second, the list of transition occupations we compile is based on historical data only. A high rate of switches clearly indicates that the skill requirements in the suggested occupation allow for feasible transitions. It also suggests that transition occupations have good labor market prospects at the time the lists are compiled. However, this does not guarantee that the prospects remain favorable at the time of the intervention. For instance, the list of occupational switches we used was

published in December 2020, four months before our experiment. Therefore, as a second step, we select occupations with a high job finding score (see Section 3.1 for details). We only include occupations in our list of suitable alternatives if they have a job finding score of at least 6. 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. Depending on a job seeker's preferred occupation, we selected 7 to 9 alternative occupations. While we generally chose the occupations with the largest number of historical switches of those that had good enough job opportunities, we left some leeway for the expertise of the employment office.

Second, it could be that the occupational switches we suggest are transitions to jobs of low quality. If the occupations we suggest are unattractive, this could explain the high vacancy to job seekers ratio. Comfortingly, we find evidence that this not the case. Using data from the Dutch Labour Force Survey, we checked the quality of the occupations we suggest. On average, the occupations we suggest offer better wages, more often full time hours and are less often jobs with temporary contracts compared to the primary search occupation. This suggests that occupational transitions could pay out in terms of job prospects and job quality.

We present the information through an information visualization that we send out to job seekers by email. In the email'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 a lot of people are looking for work in that occupation. This implies bad prospects of finding employment. 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.[9] We first list job seekers' primary occupation of interest, together with a bar of which the length and color represent the likelihood of finding a job (1).[10]

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

[10]The length of the colored bar reflects the occupation's job score. For the colors, we use the following categorization: job finding scores 2 to 4 are red, job finding score 5 and 6 are yellow,

Figure 2: Example of information email visualization



Next, 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 first show the job finding score in the same way as we did for their occupation of interest (2). Next, we show the 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

and job finding scores 7 to 10 are green.

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 much 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).[11] 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 e-mail a link to a motivational video showcasing job seekers who recently made a career transition. Since a very 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.

3.3 Randomization, data collection and timeline

We selected the sample on March 15, 2021, and ended up with 30,129 individuals who remained unemployed until the first email (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).[12] After selecting the baseline sample, we administered the pre-intervention survey followed by the intervention emails 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 UI benefits for the entire sample for 2020 - 2023. Table 2 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 alter-

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

[12] Response was incentivized through donations to charity.

Table 2: 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	Pre-survey sent	3308	3310	3292	9910
	Respondents	899	959	931	2789
April 12	First email	*Information*	*Info + video*	*No email*	
		10,075	10,050	10,004	30,129
May 10	Second email		*Only video*		
			9022		
May 28	Third email	*Information*	*Information*	*No email*	
		8388	8450	8399	25,237
June 7	Post-survey	2766	2781	2752	8299
	Respondents	400	457	421	1278
June 24	Outflow survey 1	1833	1813	1799	5445
	Respondents	579	550	588	1735
Sept 9	Outflow survey 2	1427	1402	1411	4240
	Respondents	473	491	439	1403
Dec 1	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

All dates are in 2021 unless mentioned otherwise. Minor sample selection steps were applied prior to each intervention email: 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.

native 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 4 where we present descriptive statistics.

We sent the first intervention email on April 12. It contained the information visualization for both treatment groups and the additional video link for the motivational treatment group. In Section 5.1 we provide statistics on the engagement with the email. We find that a substantial share 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. Finally, a

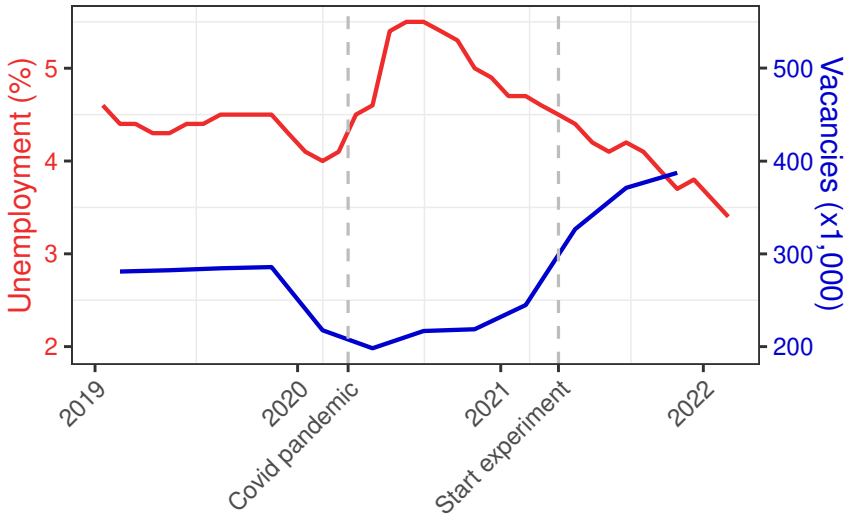
general reminder email was sent containing a modified version of the information visualization on May 28. The modification was based on clicking statistics from the first email, the details of which can also be found in Section 5.1.

To collect more information on the occupations the unemployed exit to, we also administered outflow surveys. The administrative data that we use contains start of employment spells, earnings from employment and benefits receipts. However, it does not contain information about the occupation people work in. 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. For example, for the first outflow survey (in June) 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. 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 did find a job and only then do they continue on to the survey.

3.4 Sample restrictions

For the main analyses in our paper, we impose two more sample restrictions on top of those discussed in Section 3.1. First, we restrict our main analyses to occupations with structurally poor prospects, rather than those whose poor prospects can primarily be attributed to Covid. 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 3. Until early 2020, unemployment was low and stable, while it increased to 5.5% in the summer of 2020 and steadily decreased from there. Vacancies mirror this trend. Despite our selection occupations sharing low prospects in early 2021, they differ substantially in the longer-run trends.

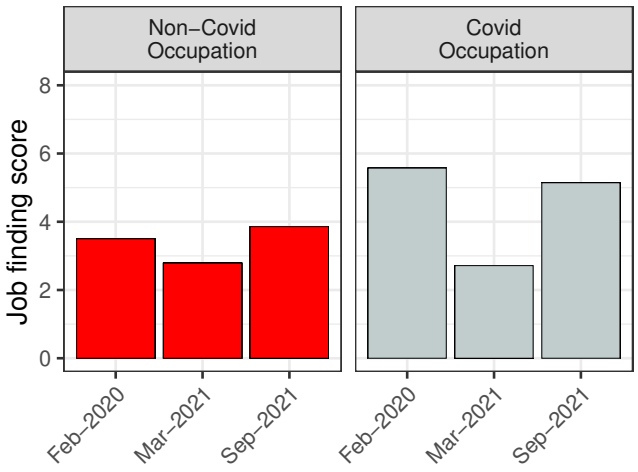
Figure 3: Unemployment and vacancies in the Netherlands



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 4, 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.

This distinction is essential for our analyses. 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. Especially since the process of transiting to a new occupation may well take several months, which is precisely the time horizon over which the labor market prospects would be expected to improve. Providing an intervention to encourage occupational

Figure 4: Job prospects covid and non-covid occupations



switches is less likely to be effective for this group.

Second, we restrict the main analysis sample to those who did not work positive hours 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 B3 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 that do not work in March 2021 (just before our intervention starts). Within this sample all characteristics are balanced between control and treatment groups. The additional advantage is that this allows us to focus specifically on those individuals that do not have a (part-time) job at the time of our intervention, which may make them more susceptive to information about potential career switches. This restriction is similar to that used in Crépon et al. (2013)[13].

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. However, unless otherwise noted, the Figures and Tables from Section 4 onwards are based on the 'Non-covid, 0-hours worked prior to the experiment' sample.

[13]They "focus on results for those who did not claim to be employed at baseline"

3.5 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 employed more often, 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 differences in rates of employment.

4 Descriptive results

Before turning to the analysis of the impact of the interventions in Section 5, 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 3 shows the characteristics of individuals in our sample, and how these change when we impose the sample restrictions mentioned in Section 3.1. 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[14] (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, whereas the other third worked positive hours. About half of selected job seekers is looking for work in a Covid occupation.

The second column of Table 3 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 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).

4.1 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. In Table A5 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 con-

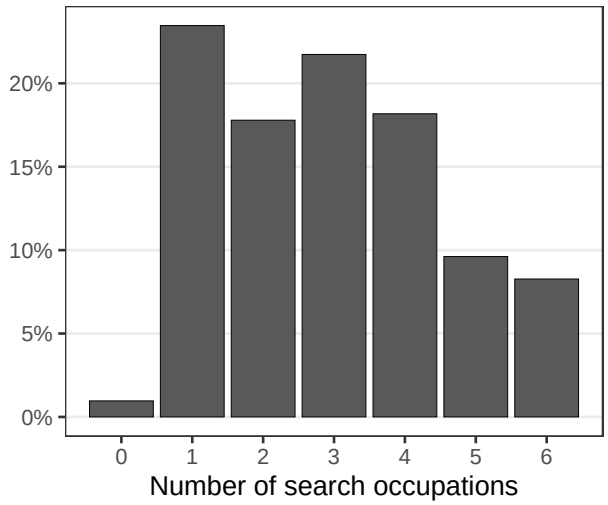
[14]This includes individuals who graduated from a 1-year vocational education program, as these are not sufficient to obtain a 'starting qualification'

Table 3: 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.

Figure 5: Number of search occupations



sider. In Figure 5 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 A7, 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 4). As the primary search occupation is for most individuals the selection occupation, it has a low job finding score (3.00, row 1).[15] 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

[15]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 4: 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.

for interviews, all of these differences are statistically significant.

4.2 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 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) 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

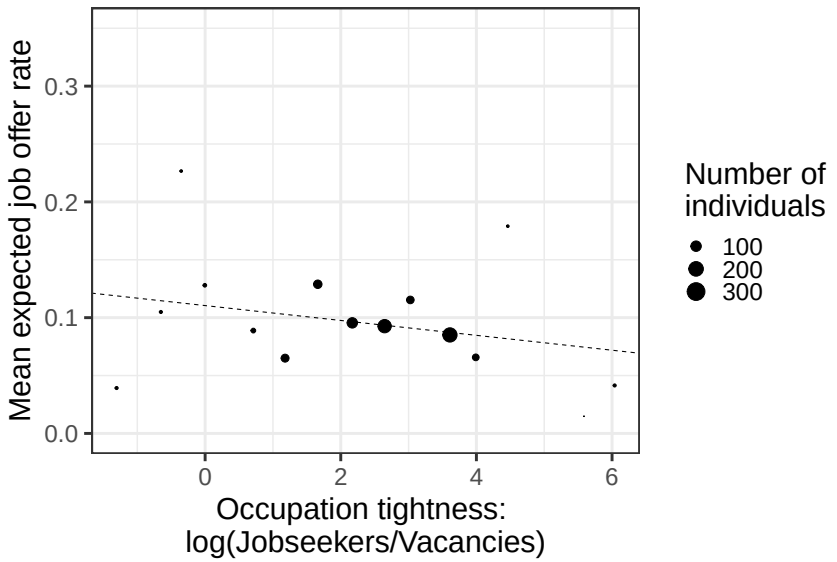
shows a large difference between the primary and alternative occupation (3.00 versus 4.29, respectively). We conclude that, on average, job seekers are not aware that job finding prospects are significantly better in their alternative occupations. Job seekers have extremely similar wage expectations for the primary and alternative occupations and also have 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. 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).

To assess 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 and expected job offer rate in Figure 6. In Panel (a) we find that this relation is fairly flat: regardless of the true tightness, the expected job offer rate of an application is always close to 0.1. A linear regression produces a small, negative but insignificant slope coefficient ($\hat{\beta} = -0.006$, p-value $= 0.14$). A further observation is that most of the alternative occupations are not occupations with the most promising tightness: most have a log-ratio between 1-4, with only a small share having very good ratios (< 1). These two facts suggest that job seekers do not select their alternative search occupations on the basis of better job prospects. First, most job seekers select alternatives with only marginally better job prospects. Second, even those who select high-prospect alternatives do not seem to be aware of these better job finding chances.

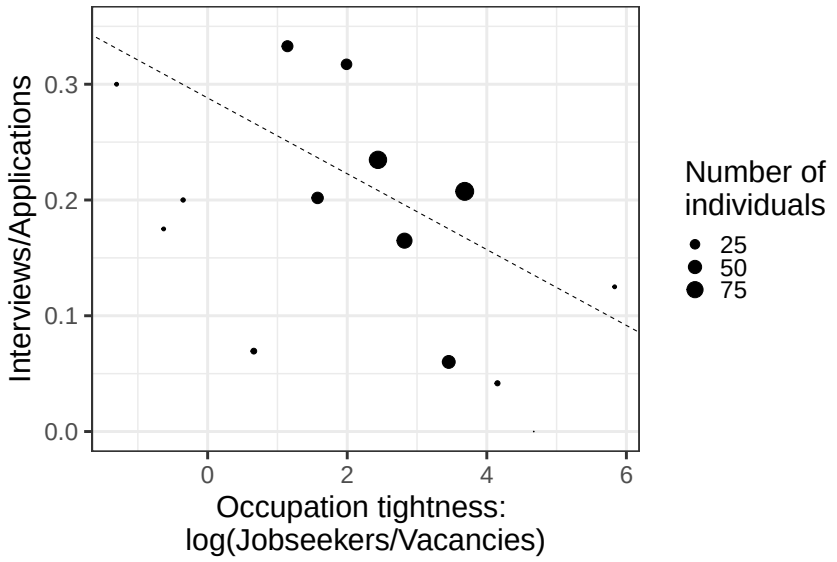
These conclusions hinge on the question whether the occupational tightness is indeed a good measure for job prospects for job seekers that have experience in other occupations. Conditional on their background, the prospects in these alternatives might not actually be so favorable. In Panel (b) of Figure 6 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. The linear regression coefficient is much larger, but not statistically significant ($\hat{\beta} = -0.033$, p-value $= 0.12$).

Figure 6: Occupational job finding prospects (with linear fit) for job seekers' first alternative occupation

(a) Expected job offer rate vs actual occupational tightness (binned scatter plot). Linear regression using all pre-intervention survey respondents (n = 463) yields slope coefficient -0.006 (p = 0.14)



(b) Actual interview rate vs actual occupational tightness (binned scatter plot). Linear regression using all pre-intervention survey respondents (n = 434) yields slope coefficient -0.033 (p = 0.12)



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 (and confident) to search in alternative occupations, 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 both encouraging for the potential of information interventions that bring the variation in job prospects to job seekers' attention. We now proceed by analyzing our intervention's impact.

5 Empirical analysis

5.1 Take-up: email opening and clicking statistics

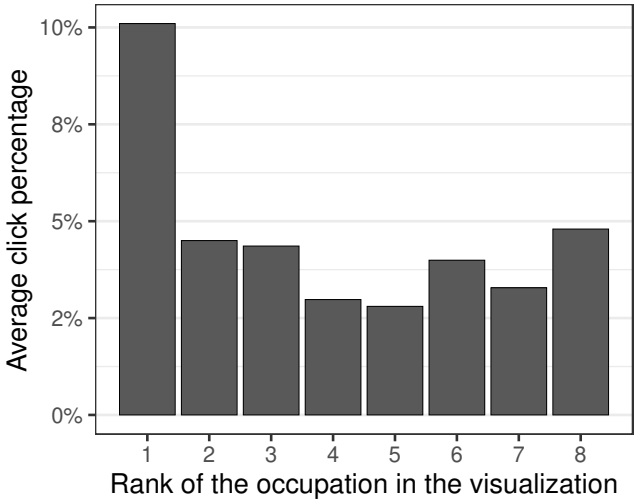
Job seekers in the treatment groups received their first email with occupational information on April 12 (see Section 3). We first compare the suggested occupations to the occupations in which job seekers report they search, to assess to what degree we provide 'new' information. Then we present statistics on engagement: whether they opened the email and clicked on the links. These statistics provide an 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 B1 in the Appendix, we show the number of suggestions that an individual received in the emails that was already present in their search set as measured in the pre-intervention survey.[16] It turns out that the vast majority (78%) searches in none of the suggested occupations before receiving the emails. 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 email (both treatment groups). From these, 12,804 opened the email (64%). Each occupation is clickable for more information about the occupation (description, tasks, skills, related occupations,

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

Figure 7: Clicking of 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 4975 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 7 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 email and (ii) that the suggestions are (primarily) ranked based on the number of historically observed transitions, suggesting that the higher placed suggestions are the most suitable ones.[17]

We sent a reminder email with a similar visualization on May 28th. In coordination with the communication experts from the employment office we decided to change the content slightly. Using the regression model from Column (3) of Ta-

[17]We can disentangle the two because the ranking was not perfectly aligned with the number of transitions. A simple regression at the occupation-level (165 observations) uncovers the importance of both rank and transitions (see Table A8 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 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.

ble A8 we generated predicted interest, controlling for the rank in the first email. 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 email. In addition only the new top-5 suggestions were included to make the message slightly shorter. The email 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 email 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 email. Of course, it might also be that job seekers are simply not interested in the video. We sent an additional email to this treatment group that *only* provided the video link (not the occupation information). This email 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.

5.2 Experimental analysis

Given the randomized assignment, the empirical strategy is straightforward and we can simply compare outcomes across the treatment and the control group. Following our pre-analysis plan, we first consider the primary outcomes, which are employment (earnings, hours and occupation) and benefit receipt. Subsequently we turn to job search behavior as measured in the post-intervention survey.

5.2.1 Balancing checks and further sample selection

Before turning to the analyses, it is worth checking whether our data is balanced on the most important dimensions. 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 A3 for our main analysis sample and Appendix Table A4 for the entire sample). In Table A6 in the Appendix, we show that the samples are also balanced in terms of responses to the pre-intervention survey.

5.2.2 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 office. 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 a specific binary point of outflow from unemployment insurance benefits. 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.

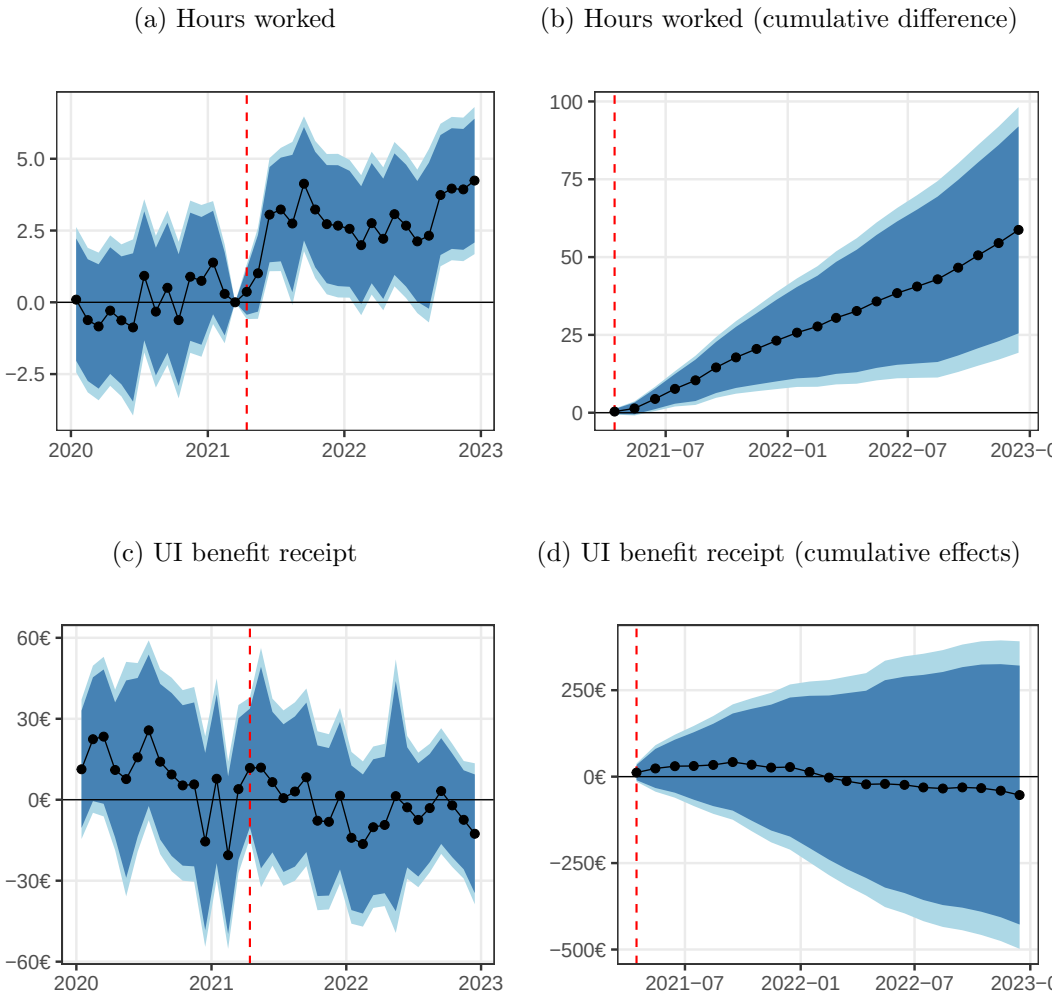
To estimate the treatment impact at various points in time, we regress the outcome measure in month t on a month fixed effect (γ_t), demographic (time-invariant) controls (X_i) with time varying coefficients, and a treatment group dummy (T_i) with time varying coefficient:

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

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 8 shows estimates of the treatment effects (λ_t) on employment, including 90 and 95% confidence intervals, for our baseline sample (job seekers in non-covid occupations that 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

Figure 8: Treatment impact on hours worked and benefit receipt

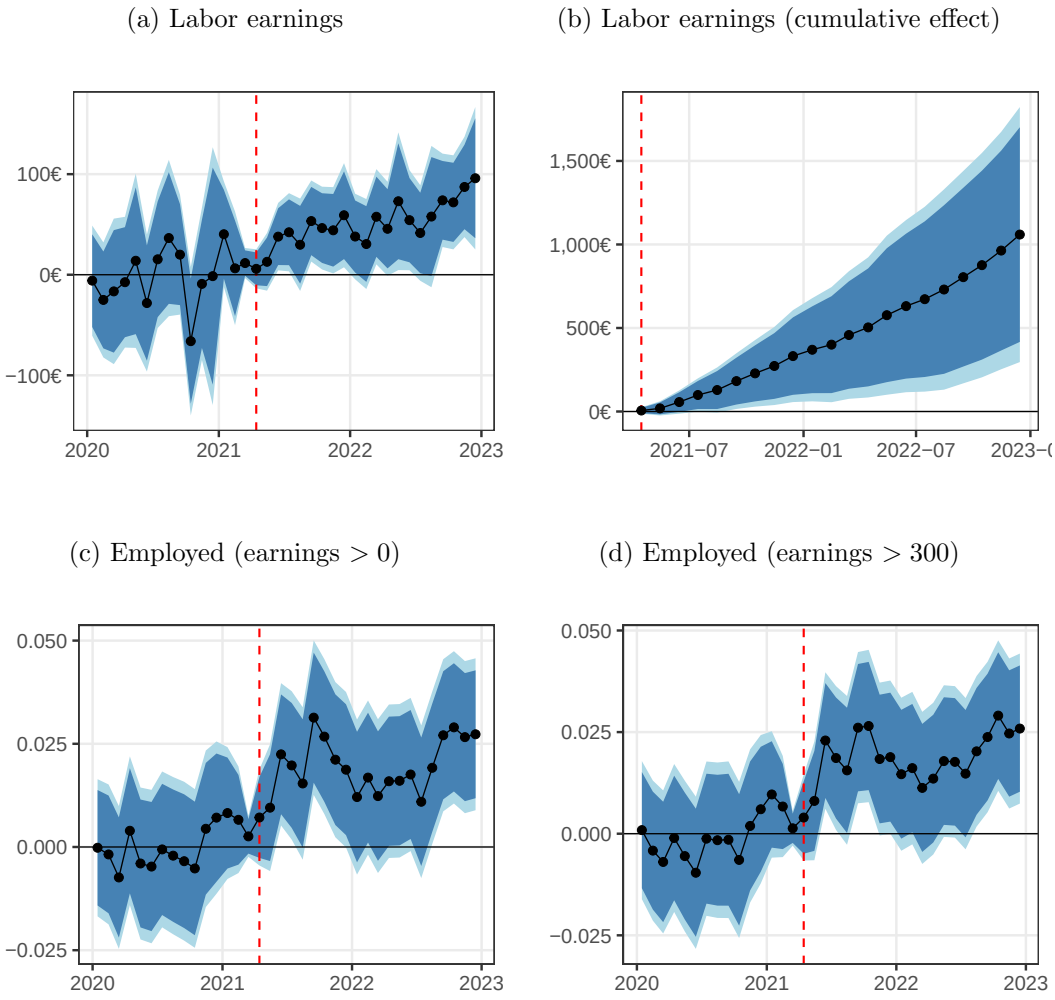


Note: Only non-covid occupations and individuals that worked zero hours in March-2021. The dashed red line indicates the first intervention email.

number of hours worked (starting from the treatment in April 2021) in panel (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

Figure 9: Treatment impact on earnings and employment



Note: Only non-covid occupations and individuals that worked zero hours in March-2021. The dashed red line indicates the first intervention email.

reduced benefit receipt. First, the hours increase may simply be 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 that, at that time, exhausted their UI benefits. The latter is particularly relevant, since we show in section 5.2.4 that the treatment impacts are larger among long-term unemployed that are likely to exhause their benefits during our observation window.

In Figure 9 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 earn-

ings grows over time, again significant at the 5% level. Toward the end of 2022, the treatment impact reaches a magnitude of around € 1100. In panels (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 B2. 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 8, panel (a)) constitutes a 3.5% increase. For labor earnings the control mean is €1040 such that the approximate €45 increase (Figure 9, panel (a)) constitutes a 4.3% increase. For employment the control mean is 54% such that the approximate increase of 1.6%-point (Figure 9, 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.

5.2.3 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 analyse our outflow survey. As described in more detail in Section 3.3, 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 5: 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	

Only non-covid occupations and individuals that worked zero hours in March-2021. Figures are aggregates across all outflow survey waves (see Table 2 for details).

proxy of job finding.[18] As a result, the survey provides occupational information for individuals that (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.

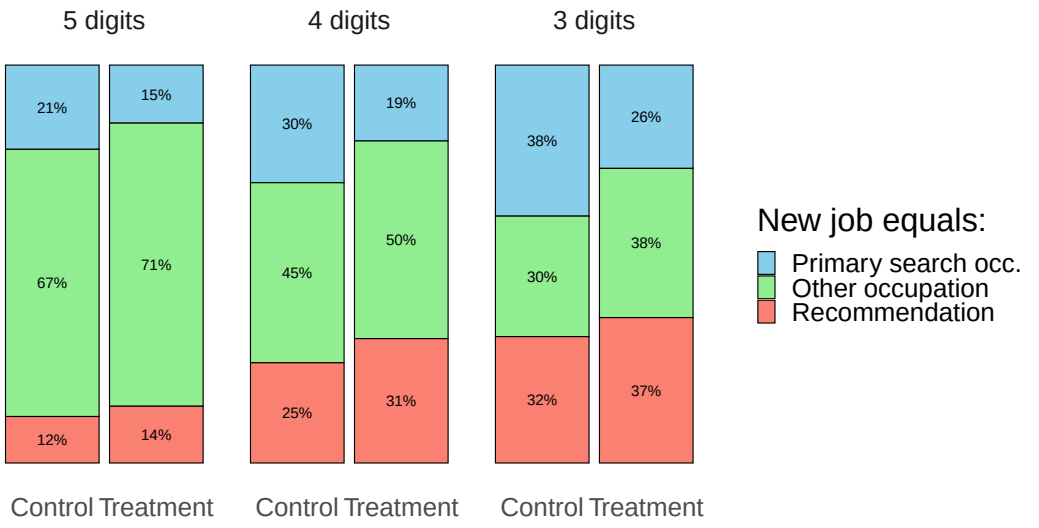
Table 5 provides a summary of the response to the survey. Of the 10,738 individuals in our non-Covid subsample, 4,452 (41%) received an invitation to fill out the outflow survey. The first row shows that the share of treated individuals who received an invitation is slightly higher (42.0%) than that 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 higher invitation rate also translates in a higher survey opening rate, which is statistically significant. 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 difference is statistically significant, suggesting that either the job finding rate was indeed slightly larger in the treatment group, or that our treatment boosted the survey response rate. The latter might create selection bias in the responses to which we return in a moment (but note that the difference is small, limiting the magnitude of potential selection bias).

Figure 10 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 selection 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 level

[18]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.

at which selection took place), 4-digit, and 3-digit[19].[,] [20]

Figure 10: Comparison of occupations of new jobs with the primary search occupations and the set of recommendations (at different occupational digit levels)



Note: Only 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 occupations equal to the 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 the 4-digit and 3-digit level, this difference further increases to 11 and 12 percentage points (both strongly statistically significant). At the 4-digit

[19]The survey asked for a free text job title, which were blindly coded into a 5-digit occupational code.

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

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 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 5, 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.[21]

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.

5.2.4 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 (see **??**), 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 11, 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

[21] 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 10, 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%).

but smaller and statistically insignificant for the short-term unemployed in panel (b). Also 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).

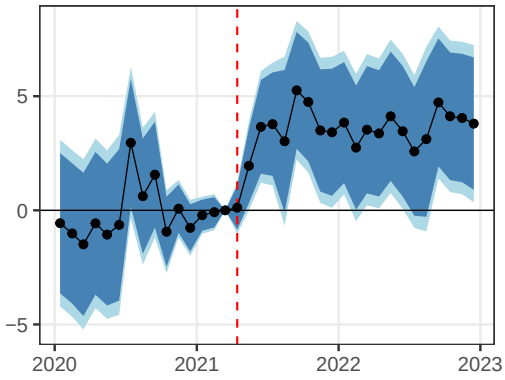
These compelling results raise the question whether it is the longer unemployment duration perse that drives the responsiveness to information about alternative occupations, or whether dynamic selection alters the composition of the sample relative to short-term unemployed. In Table A9 in the appendix 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 A10 in the appendix).

5.2.5 Treatment effects on job seekers with employment at the time of intervention and for job seekers in 'Covid' occupations

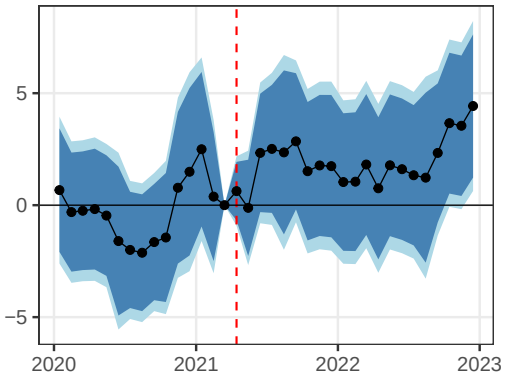
While we consider the results in Section 5.2.2 to be our main results, it is worthwhile to investigate how the treatment affected working job seekers and job seekers looking for work in the 'covid occupations' (occupations that quickly recovered after the Covid-19 pandemic). Table 6 shows the treatment effect on a range of outcomes measured 18 months after the intervention. For comparison, the first row shows 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-

Figure 11: Heterogeneous treatment impact by unemployment duration

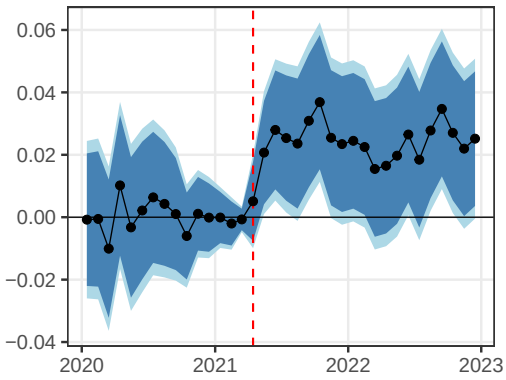
(a) Hours worked: long duration



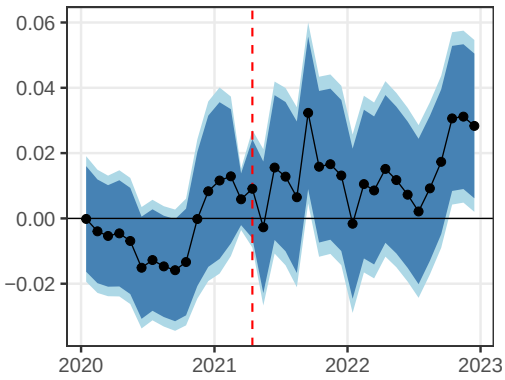
(b) Hours worked: short duration



(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 email.

Covid levels. Figure B4 in the Appendix shows that the latter explanation is more likely. While Figure 10 shows that treated individuals in non-covid occupations find jobs in different occupations than those in the control group, Figure 10 shows that this is not the 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.

Table 6: 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.

The last row of results shows the impact for those who already held a part-time 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 that were already employed were much less likely to be affected by the treatment.

5.2.6 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 employment service platform. Job seekers face a requirement to complete at least four activities every four weeks. These activities can consist of applications, but also other search activities count (e.g. network meetings, open

inquiries with employers, etc.). 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 connections). 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. Therefore, we simply re-estimate equation 1, using the number of applications registered per month as the outcome.[22] We present the estimates in panel (a) of Figure B5 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 email 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 employment services 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) for individuals from our sample that use the platform while being logged in, between March-June 2021. The advantage of these data is that they 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) sample does so. In an attempt to obtain insights from the data, we first restrict our analysis to all individuals that 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 B5 in the appendix show that there is no indication of a treatment effect. The number of viewed vacancies is

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

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.

5.2.7 Treatment effects on survey responses

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

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

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 7 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 (Column 1), (2) total number of weekly applications (Column 2), (3) total number of weekly interviews (Column 3), (4) number of occupations included in the search (Column 4), (5) the mean job finding score of the set of search occupations (Column 5) and (6) the number of suggestions from the email that are included in the set of search occupations (Column 6). We find that the treatment effect estimate (β_2), 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.

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

Table 7: 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)
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 email that are included in the set of search occupations (Column 6).

(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 seem to have found employment in occupations different from their initial occupation of interest more often. There are a number of possible explanations for the null effects 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, the sample that 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. Obtaining administrative data on job search activities as registered by case workers and through logged activities on the national job search website is ongoing. These data are arguably more precise and will be available for the entire sample.

Table 8: 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 group	−0.008	0.030	−0.012	0.040	0.068*
	(0.059)	(0.089)	(0.034)	(0.039)	(0.038)
Post-period	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)
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 email that are included in the set of search occupations (Column 5).

6 Conclusion

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. Combining administrative data with pre- and post-intervention surveys to collect labour market beliefs, we measure how this intervention may contribute to opening up job seekers' job search horizon and stimulate them towards occupational mobility to jobs with better prospects.

Our descriptive statistics show that our sample of job seekers is likely to respond to the information treatment. While many report to be willing to explore new alternatives and are confident about their ability to work in a new occupation that matches their skillset, actual job search is fairly narrow in terms of occupations. Moreover, beliefs about job offer rates show that unemployed job seekers' awareness of the large variation in labor market prospects across occupations is very limited.

We find significant effects of our intervention on unemployed job seekers in structurally poor occupations, with increases in employment, hours worked and

earnings all between 4% and 5%. We do not find such effects on workers in Covid occupations for which the poor labor market prospects were short-lived.

Our intervention, we argue, is relatively inexpensive and can be easily replicated. It is low cost, even on a very large scale, because it relies on information that is already available at public employment services: information about job seekers to vacancy ration by occupation and information on occupation to occupation mobility. It is easy to replicate since it requires no specific technologies and relies on making available, relevant data easily accessible and understandable for job seekers.

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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 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 A3: 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 A4: 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 A5: 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 A6: 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 A7: 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

Only 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 emails. The variables with a 1-5 scale were answered using Likert scales (1 = Strongly disagree, ..., 5 = Strongly agree).

Table A8: 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^{***}	0.04^{*}
	(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 A9: 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	

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

Table A10: 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	

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. Remaining benefits and unemployment duration are measured in March 2021.

Appendix B: Additional Figures

Figure B1: Comparing suggestions and initial search occupations

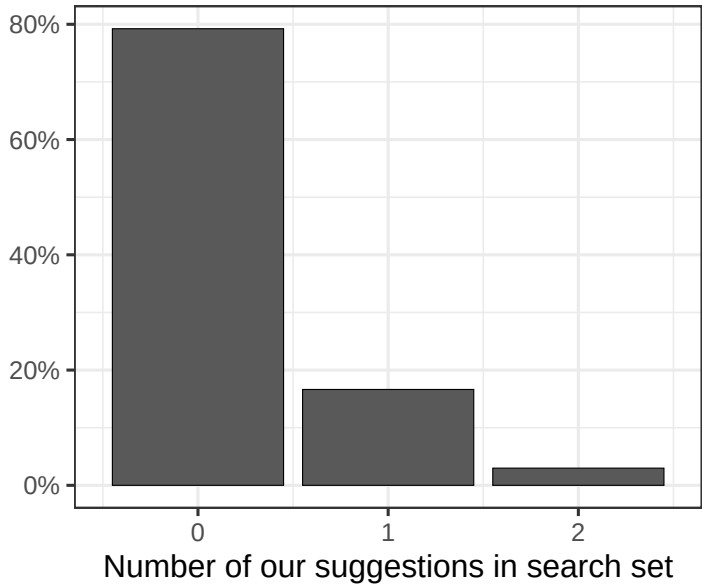
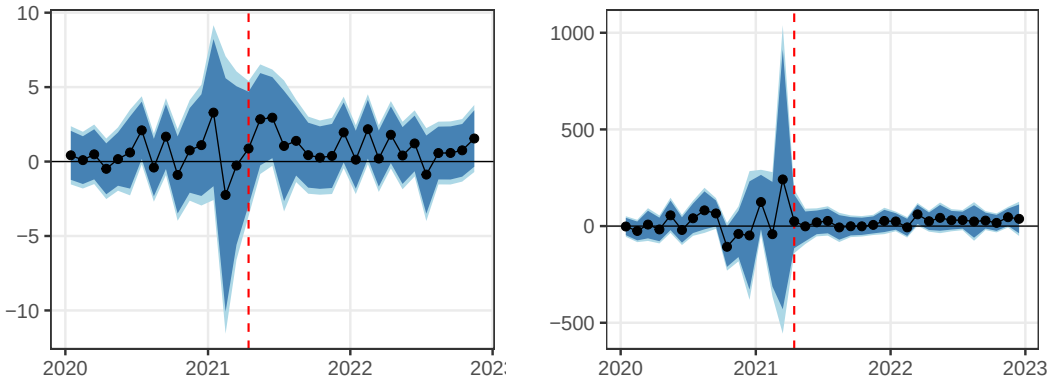


Figure B2: Intensive margin effects: treatment impacts conditional on employment

(a) Hours worked, conditional

(b) Labor earnings, conditional

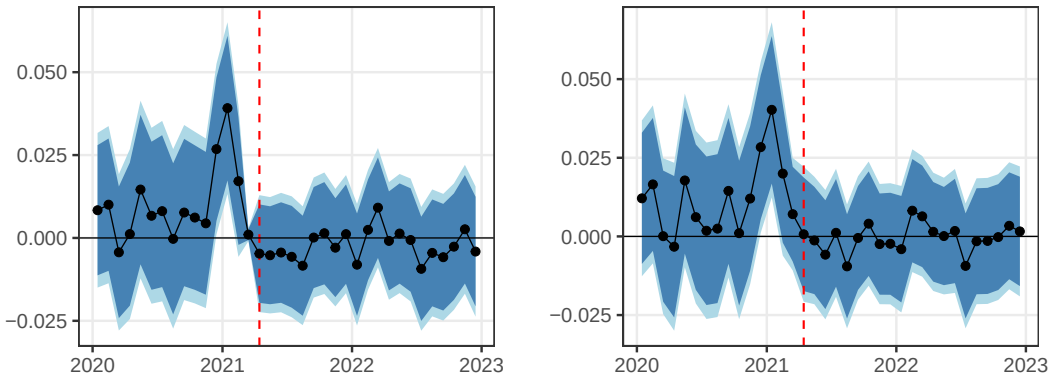


Note: The left panel considers only observations where the individual has positive working hours. The right panel considers only observations where the individual has positive labour earnings. Individuals in non-covid occupations without employment in March-2021. The dashed red line indicates the first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

Figure B3: Hours worked by month for job seekers working positive hours before treatment

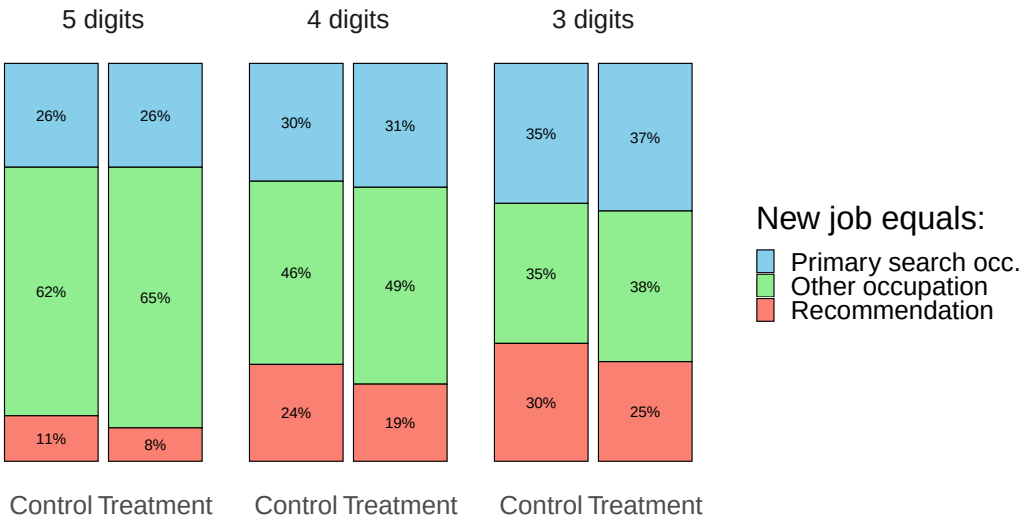
(a) Employment (hours ¿ 0)

(b) Employment (hours ¿ 300)



Note: Individuals in non-covid occupations with employment in March 2021. The dashed red line indicates the first intervention email.).

Figure B4: 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

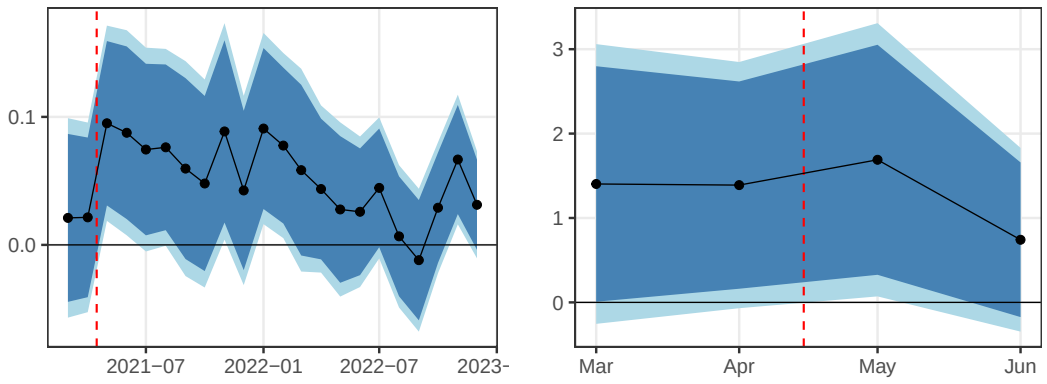


Note: 'Primary search occ' report the share of individuals who found work in the same occupation as their initial 'primary occupation of search' (registered at time of registration for UI benefits). 'Recommendation' reports the share of individuals who found work in one of the occupations recommended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

Figure B5: Treatment impact on monthly job search: registered applications and online viewed vacancies

(a) Registered applications

(b) Online search: viewed vacancies



Note: Individuals in non-covid occupations without employment in March 2021. The dashed red line indicates the first intervention email.).

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.