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. The information is provided through a personalized email containing suggestions about suitable alternative occupations and how the prospects of these alternatives compare to the job seekers' current occupation of interest. We additionally include 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. Our email is opened by the vast majority of job seekers, revealing the alternative suggestions. The motivational video link is rarely used. Effects on unemployed job seekers in structurally poor labor markets are large: over the 20 months following the intervention, treated job seekers are 2.5 percentage points more likely to be employed, work over 50 more hours, and earn €800.- more. Additionally, they are more likely to end up in a different occupation than they initially targeted. There is little impact on job seekers in occupations which did well prior to and after the Covid-19 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 (del Rio-Chanona, Mealy, Pichler, Lafond, & Farmer, 2020; Forsythe, Kahn, Lange, & Wiczer, 2020), technological development, and automation (Autor, Levy, & Murnane, 2003; Autor, 2015; Brynjolfsson, Mitchell, & Rock, 2018; Frey & Osborne, 2017) have been associated with profound changes in the demand for certain occupations. 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, Kircher, and Muller, 2019; Faberman and Kudlyak, 2019), and this can be problematic when search occupations are in low demand.

In this paper, we design and evaluate two low-cost digital interventions aimed at job seekers who are looking for work in occupations that are in low demand. The first intervention aims at addressing informational deficits. The second aims at tackling psychological barriers to occupational transitions. We conduct these interventions in collaboration with the Public Employment Office in the Netherlands (UWV).

The experiment involves 30,129 job seekers who recently became unemployed and search in one of 21 occupations with poor employment prospects. We send an email to 20,125 of these job seekers, in which we inform them of the poor job prospects in their primary occupation of interest and suggest alternative occupations with better prospects that are particularly well-suited to their occupational or skills background. For each suggested occupation, we include 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. In addition, the email contains a link to an online job search engine that job seekers can use to find relevant vacancies. 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 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.

We measure the impact of the interventions on benefits receipts, earnings and job finding probability using administrative data.[1] 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.

Note that our focus is unemployed who search employment in low demand occupation, but not on unemployed with a narrow search, which could lead to a null-effect because a narrow search could reflect a personal comparative advantage of search friction (Moscarini, 2001). In fact, analyses of survey data we gathered show 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 also do not force unemployed job seekers to broaden their job search, but do make suggestions of suitable switches with better prospects to them. Imposing a broader job search could reduce job finding rates (van der Klaauw, 2022).

Take-up of the information emails is high: we find that more than 60% of the treatment group opened the two informational emails. A sizeable share also clicked on at least one occupational suggestion for more information. The motivational video, on the other hand, did not attract interest. After an explicit

[1] 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.

reminder still fewer than 10% of the recipients watched the video.

For unemployed job seekers interested in occupations with structurally poor labor market prospects (i.e., before, during, and after the Covid-19 pandemic), we find large effects of the intervention on employment and earnings. In the 20 months following the intervention, job seekers in these labor markets are about 2.5 percentage points more likely to be employed, work about 50 additional hours during this time, and earn €800 more. Based on survey data, we also find that these job seekers are more likely to end up in a different occupation than the one they were initially searching for work in. For job seekers in occupations for which demand rebounded after the Covid-19 pandemic, we do not find any impact of the intervention.

Our first treatment contributes to the literature on advice and counseling. van der Klaauw (2022), e.g., investigate the impact of an intensified counseling intervention to conclude that meetings with counselors increase job finding but that imposing broader search has adverse effects. Other than that, little is known about this topic, as these policies are often combined with other policies such as monitoring and sanctions, making it difficult to disentangle underlying mechanisms (see Card, Kluve, and Weber (2018) for a recent review). Earlier literature has shown that subjective expectations about job finding prospects determine individuals' search efforts (Caliendo, Cobb-Clark, & Uhlendorff, 2015). However, these expectations are not always in line with reality, which may explain why individuals tend to spend too much time looking for work in low-demand occupations. Individuals partly form their beliefs through lived experiences (see, e.g., Jäger, Roth, Roussille, and Schoefer (2022), who show that individuals strongly anchor their wage beliefs to current earnings), but they also actively seek information.

Information acquisition is an endogenous process (Wiederholt et al., 2010). Individuals only acquire information when they deem it to be worthwhile. In the case of labor market prospects, individuals will want to acquire more information if they have high macroeconomic risk exposure (Roth, Settele, & Wohlfart, 2022). This leads to a Catch-22 situation. Individuals who are unaware of the poor labor market prospects in their occupation of interest see no reason to search for information about more promising alternatives, and as such remain uninformed. Directly providing these individuals with information can be effective, as individuals do update their beliefs and behavior based on relevant information they receive (Roth & Wohlfart, 2020).

Related to this paper, Altmann, Falk, Jäger, and Zimmermann (2018) evaluate the effects of a generic information intervention in Germany. They sent a brochure aimed at providing generic information about beneficial job search activities and motivate job seekers to exert more search effort early on in their unemployment spell. They find that this intervention is effective for job seekers at risk of long-term unemployment. Our study builds on previous work by Belot et al. (2019), who test information interventions on a small sample of job seekers in the UK. They observed job seekers' search behavior over the course of 3 months and 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 aims at an evaluation of the effects on the chances of finding employment. In addition, we collect detailed information on beliefs regarding employment prospects, allowing us to investigate the mechanism underlying the impact of providing labor market information.

Our second (motivational) intervention draws on the literature on social norms and role models. The social norm to work is a strong motivator to find employment (Kondo & Shoji, 2019). Role models may convey such social norms, as well as motivate individuals and display that certain career paths are possible. Earlier studies have shown that role models can be effective in shaping individuals' choices (e.g., Del Carpio and Guadalupe, 2021 and Porter and Serra, 2020; Riley, 2022). Our setting is unique in that it combines factual information (targeting individuals' beliefs about the labor market) with a more intangible part focusing on more personal aspects through role models (targeting individuals' beliefs about their own ability and chances of finding different employment).

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

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 register with the Dutch Public Employment Agency in order get access to unemployment benefits. Upon registration, unemployed get access into a online 'work folder' in which they register relevant information (such as CV) and a questionnaire about 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, 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 discuss their job search with work counsellors. Much of this communication takes place online, via the 'work folder', and via email sent from that platform.

To support job search activities, 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), 2015). 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.[2] 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. Both pieces of information are updated yearly, and we explain below how they are computed. While job seekers can consult labor market information on these two websites, it is scattered throughout the websites. Moreover, the websites is not personalized, meaning job seekers have to be well aware of their wants and needs to find relevant information. In our experiment, we (i) consolidate the available – and add new – labor market information about occupations, and (ii) provide this information in a personalized manner through email.

3 Experimental Design

3.1 Sample selection

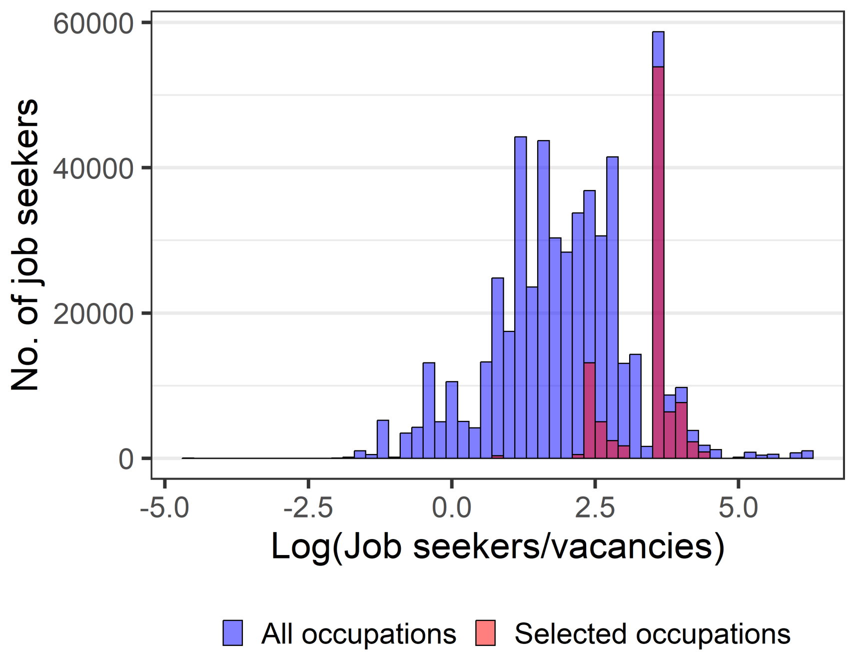
The aim of our experiment is to help unemployed job seekers who search in occupations with low employment prospects to consider different, more promising, occupations. We evaluate the effectiveness of an information and a motivation treatment through a large-scale randomized controlled trial in collaboration with the Public Employment Office in the Netherlands (UWV).

The first step in constructing the sample of job seekers is to select the occupations that offer poor job prospects. Job seekers who search in these occupations are most likely to benefit from information on alternative occupations with better prospects. For this, 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 on a yearly basis. These scores are computed for over 600 narrowly defined occupations (5-digit classification).[3] The

[2]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

[3]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.

Figure 1: Labour market tightness of selected and other occupations



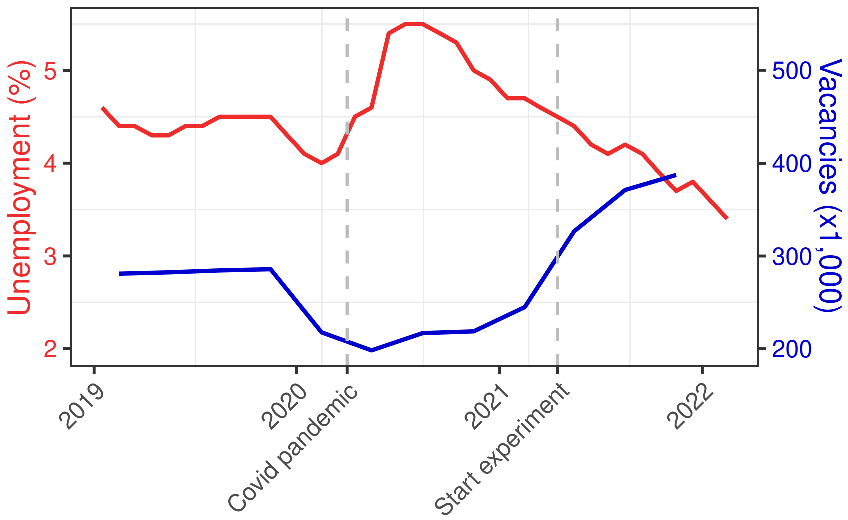
score runs from 2 (very poor job prospects) to 10 (excellent job prospects). For the experiment, we selected all individuals interested in occupations with a score of 2, 3 or 4 in the spring of 2021, leading to 21 'selection occupations'. These 21 occupations exhibit a substantial variety: they include low-skilled occupations such as waiters/bartenders, janitors and taxi drivers, but also skilled professions such as graphic designer, event organizers and social workers. The complete list can be found in Table 2 (including their relative share within the sample). Appendix Table A1 provides the original occupation names in Dutch. Figure 1 shows the distribution of market tightness (the log of job seekers/vacancies) for the primary search occupation of all unemployed job seekers.[4] The 21 selected occupations are highlighted in red, demonstrating that we selected occupations with the highest job seeker to vacancy ratios.[5]

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 2. Until early 2020, un-

[4]Source: UWV Open Match Data (https://data.overheid.nl/en/dataset/uwv-open-match-data)

[5]Note that 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.

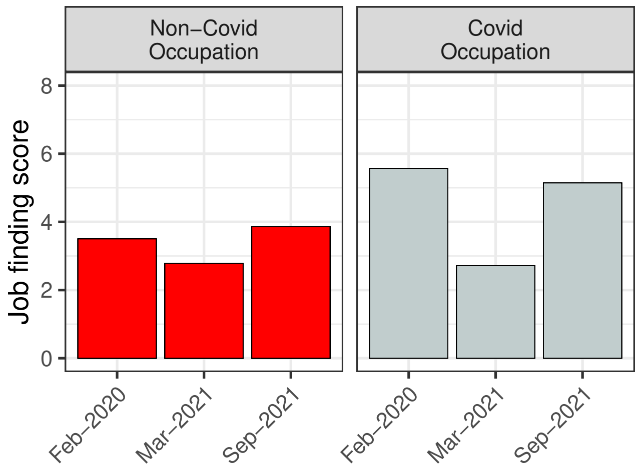
Figure 2: Unemployment and vacancies in the Netherlands



employment 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. Most importantly, there was large variation in the degree to which occupations were affected by the varying 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. There are 7 'Covid occupations' and 14 'Non-covid occupations'. In Figure 3, 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,

Figure 3: Job prospects covid and non-covid occupations



which is precisely the time horizon over which the labor market prospects would be expected to improve. Providing an intervention to encourage occupational switches is less likely to be effective for this group.

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 considered 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.

3.2 Interventions

3.2.1 Information treatment

Our first treatment objective 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. While a high rate of switches is a clear indication that the skill requirements in the suggested occupation are such that transitions are possible and that transition occupations have good labor market prospects at the time the lists are compiled, it does not guarantee that prospects are still good at the time of the intervention (e.g., the list of occupational switches we use was published in December 2020, 4 months prior to 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.

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 job 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

Figure 4: Example of information email visualization

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 4 shows an example of the visualization we use. We first list job seekers' primary occupation of interest, together with a bar of which the length and color represent the likelihood of finding a job (1).[6]

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 opportunities 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 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 (25^{th} percentile of automation risk or lower), we mention this to the job seeker (4).[7] Lastly, there is a link for more information about the occupation (extended description, required certifications, various job titles, etc.) (5).

3.2.2 Motivation treatment

The second intervention targets 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 is 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 per-

[6] For the length, we divided the full length of the bar (in grey) up into tenths. Depending on the occupation's job finding score, it fills up the corresponding share of the bar. For the colors, we use the following categorization: job finding scores 2 to 4 are red, job finding score 5 and are yellow, and job finding scores 7 to 10 are green.

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

sonal 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.

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).[8] 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. Table 1 provides a precise timeline with corresponding sample sizes.

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

[8]Response was incentivized through donations to charity.

Table 1: Timeline experimental set-up and sample sizes

Date	Event	Treatment 1 (Information) N = 10,050	Treatment 2 (Info + video) N = 10,075	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*	
		10,050	10,075	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	1256
	Respondents	106	107	136	349
August 30 (2022)	Outflow survey 5	402	411	389	1202
	Respondents	130	118	104	352

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.

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 euro 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 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 5.2, we first provide descriptive statistics for our sample and document a range of descriptive findings regarding job search behavior and beliefs in our data. In Table 2 we show that the job seekers in our sample have a fairly long unemployment duration at the time of selection, with a mean of 32 weeks. This is not surprising, given that we selected job seekers from those occupations with the worst job finding prospects. Most job seekers still are entitled to substantial benefits (51 weeks on average). Our selection of occupations also resulted in a skewed gender distribution, with only 25% males and 75% females. The distribution across selection occupations shows that bartenders/waiters, office support staff and receptionists are by far the largest groups and in all of these women are over-represented. As stated in Section 3.1, seven of these occupations can be classified as 'Covid occupations', which are occupations which were hit particularly hard by the Covid pandemic.

4.1 How do job seekers search?

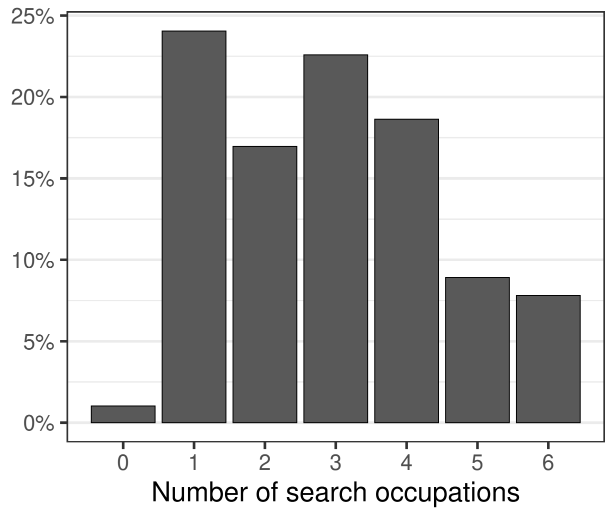
For the subsample that completed the pre-intervention survey (N = 2,789) we obtain a rich set of responses regarding job search beliefs and activities. While those invited to the survey were randomly selected, those who responded may not be. In Table A3 in the Appendix, we compare the survey respondents 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

Table 2: Sample descriptives: administrative data

	Mean	Std.Dev.	Min	Max
Male	0.25	0.43		
Unemployment duration (wks.)	32.17	28.07	0.00	463.00
Remaining benefits (wks.)	50.98	29.70	4.14	188.71
Covid selection occ.	0.49	0.50		
Selection Occupation:				
Non-covid occupations				
Activity counsellor	0.03	0.18		
Archivist	0.01	0.10		
Video and sound technician	0.01	0.10		
Janitor/Concierge	0.03	0.17		
Animal caretaker	0.01	0.12		
Printer	0.01	0.10		
Graphic designer	0.03	0.16		
Office support staff	0.21	0.41		
Primary school teaching assistant	0.02	0.15		
Event/conference organizer	0.02	0.15		
Producer (television/film)	0.01	0.09		
Social worker	0.08	0.27		
Steward/stewardess	0.01	0.10		
Shop attendant household/leisure	0.01	0.12		
Covid occupations				
Hotel receptionist	0.02	0.13		
Hairdresser	0.02	0.14		
Bartender/waiter	0.16	0.37		
Canteen/Buffet employee	0.07	0.25		
Receptionist	0.17	0.37		
Travel agent	0.02	0.13		
Taxi driver	0.05	0.21		
Observations	30,129			

Remaining benefits and unemployment duration are measured in March 2021.

Figure 5: Number of search occupations



difference in the distribution across selection occupations. Based on observable characteristics, we conclude that we can interpret the survey responses as fairly representative of the full experimental population.

Survey respondents first indicate what their primary search occupation is (typically the selection occupation) and which alternative occupations they consider. In Figure 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 A4, we show that most respondents (i) spend at least some hours per week exploring alternative occupations, (ii) are fairly willing to consider new occupations, (iii) have quite some confidence in their ability to work in an occupation in which they have no experience, and (iv) believe that their skills are transferable. Over 50% of respondents expects to widen their search in terms of occupations if they are still unemployed in two months.

For the primary and first alternative search occupation, we collect various measures of job search activities and elicit beliefs about the returns to job search (see Table 3). As the primary search occupation is for most individuals the selection occupation, it has a low job finding score (3.2, row 1).[9] The first alternative occupation that they search in offers better prospects with an average job finding score of 4.3. In the previous two weeks the average number of applications for

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

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

	Primary (N=2789)		Alternative (N=2789)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	p
Job search activities:						
Job finding score	3.20	1.02	4.26	1.67	1.06	0.00
Applications sent (past 2 weeks)	3.14	6.16	2.51	4.78	-0.64	0.00
Job interviews (past 2 weeks)	0.43	1.32	0.37	1.04	-0.06	0.12
Interviews per application	0.16	0.43	0.20	0.45	0.04	0.01
Expectations:						
Expected job offer rate	0.10	0.11	0.10	0.11	0.00	0.67
Expected wage	2638.27	866.48	2698.29	1003.90	60.02	0.03
Reservation wage	2563.07	878.22	2596.49	933.67	33.42	0.21
Job stability	0.68	0.30	0.71	0.27	0.03	0.00
Exp. appl. if equal job offer rate	4.20	7.81	4.47	8.39	0.28	0.29
Exp. appl. if equal wage	4.28	7.59	4.41	7.99	0.13	0.62
Exp. job offer rate in 2 months	0.09	0.10	0.08	0.10	-0.01	0.11

"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.

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: 0.43 for the primary occupation and 0.37 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. Expect for interviews, all of these differences are statistically significant.

4.2 How well are job seekers informed about job prospects?

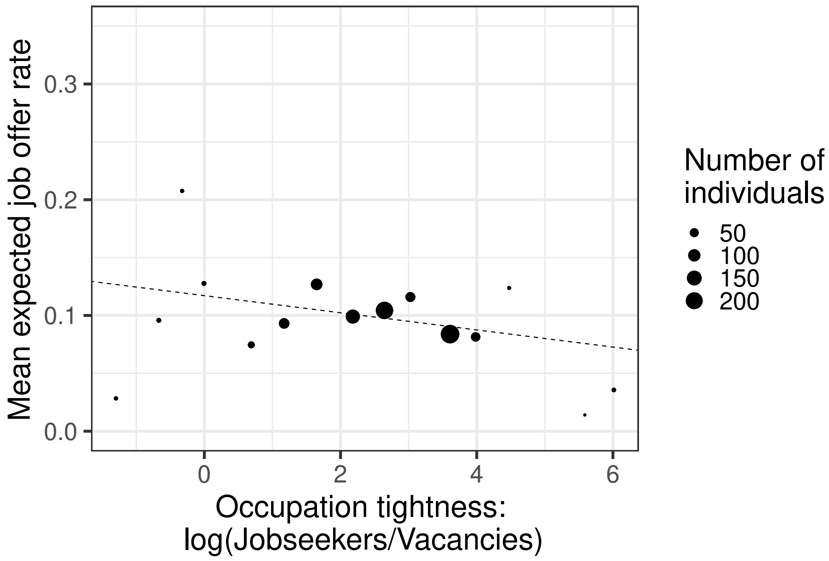
We elicit a range of beliefs about the returns to job search activities and labor market prospects. The key question of interest is whether expectations regarding job prospects in various occupations align with actual prospects. In addition, we explore whether these expectations drive job search activities. 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 (0.10, 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 (3.20 versus 4.27, respectively). We conclude that, on average, job seekers are not aware that job finding prospects are significantly better in their alternative occupations. Job seekers also expect to earn higher wages in the first alternative occupation and have a slightly higher reservation wage for the alternative, although the difference is not significant. 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 0.09 for the primary occupation (compared to 0.10 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 positive and marginally significant slope coefficient ($\hat{\beta} = -0.007$, p-value = 0.05), but the magnitude is very small. 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.

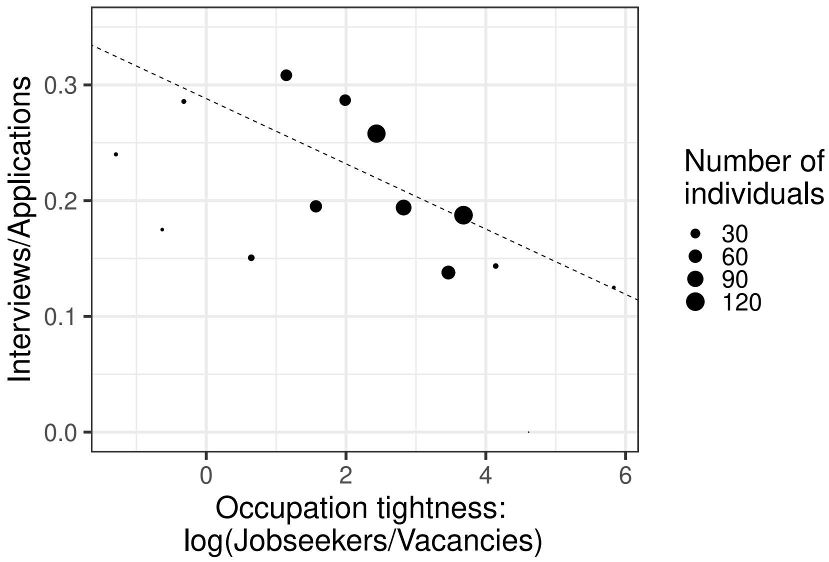
These conclusions hinge on the question whether the occupational tightness is indeed a good measure for job prospects for job seekers that have experience in other occupations. Conditional on their background, the prospects in these alternatives might not actually be so favorable. In Panel (b) of Figure 6 we

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 = 634) yields slope coefficient -0.007 (p = 0.05)



(b) Actual interview rate vs actual occupational tightness (binned scatter plot). Linear regression using all pre-intervention survey respondents (n = 571) yields slope coefficient -0.028 (p = 0.12)



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 ($\hat{\beta} = -0.028$, p-value = 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

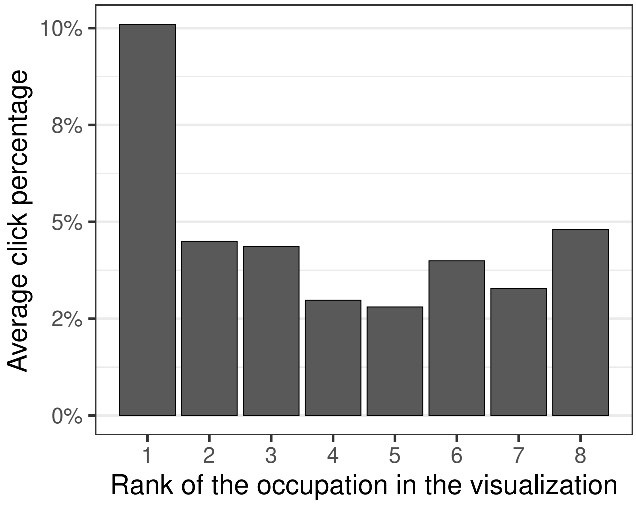
5.1 Take-up: email opening and clicking statistics

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.[10] It turns out that the vast majority (78%) searches in none of the suggested occupations before receiving the

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

Figure 7: Clicking of occupations



emails. A small group was already searching in one of our suggested occupations (18%) and a negligible share already searches in 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, 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.[11]

[11] 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 A2 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

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 Table A2 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 section will 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

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.

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. As randomization was stratified by gender, unemployment duration (in three bins) and selection occupation, we obtain near-perfect balance on these variables, as we show in Appendix Table A5. In Table A6 in the Appendix, we show that the samples are also balanced in terms of responses to the pre-intervention survey.

The significant differences 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. For completeness we provide treatment effects also for the excluded individuals: those that work a positive number of hours in March 2021.

As stated before, a number of our selection occupations recovered swiftly after most Covid-restrictions were lifted. As such, demand for these occupations strongly increased again. Since individuals who were looking for work in these occupations are likely to be able to find a job in that occupation again, the treatment is likely not as effective for them and does not align with our initial question of interest. As such, we focus our analyses only on individuals looking for work in Non-covid occupations. Tables A7 and A8 show that this subsample is balanced on all relevant variables as well.

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.

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:

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

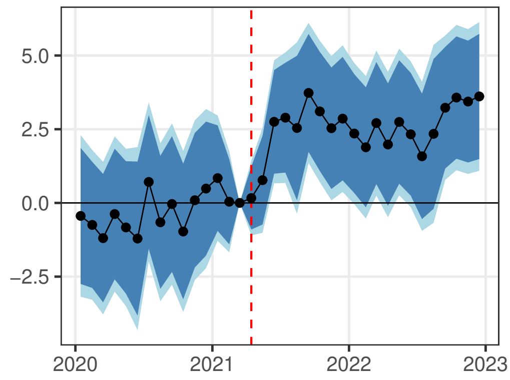
Standard errors are clustered at the individual level and the months t run from January 2020 (14 months prior to the treatment) until December 2022. The pre-treatment months are included as an additional check of adequate randomization between treatment and control groups. Covariates X_i are included 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 the sample 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 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 employment.

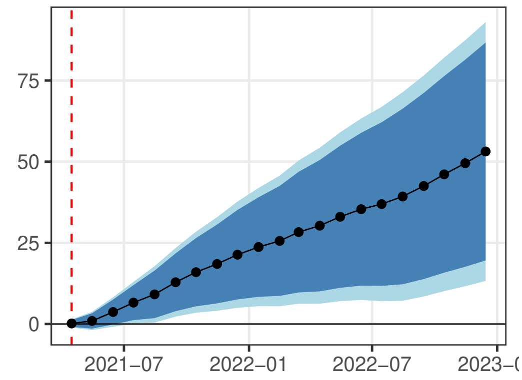
Benefit dependence is assessed in panel (c), where the outcome is monthly UI benefit receipt (in €). We find no indication of a treatment impact, with the post-treatment coefficients close to zero and never statistically significant. The lack of results also translates into cumulative UI benefit receipt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

Figure 8: Treatment impact on hours worked and employment: individuals without employment in March-2021

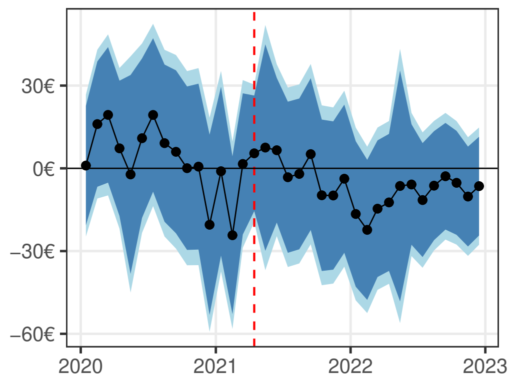
(a) Hours worked



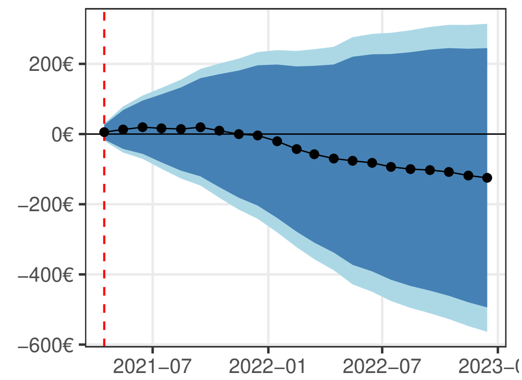
(b) Hours worked (cumulative difference)



(c) UI benefit receipt

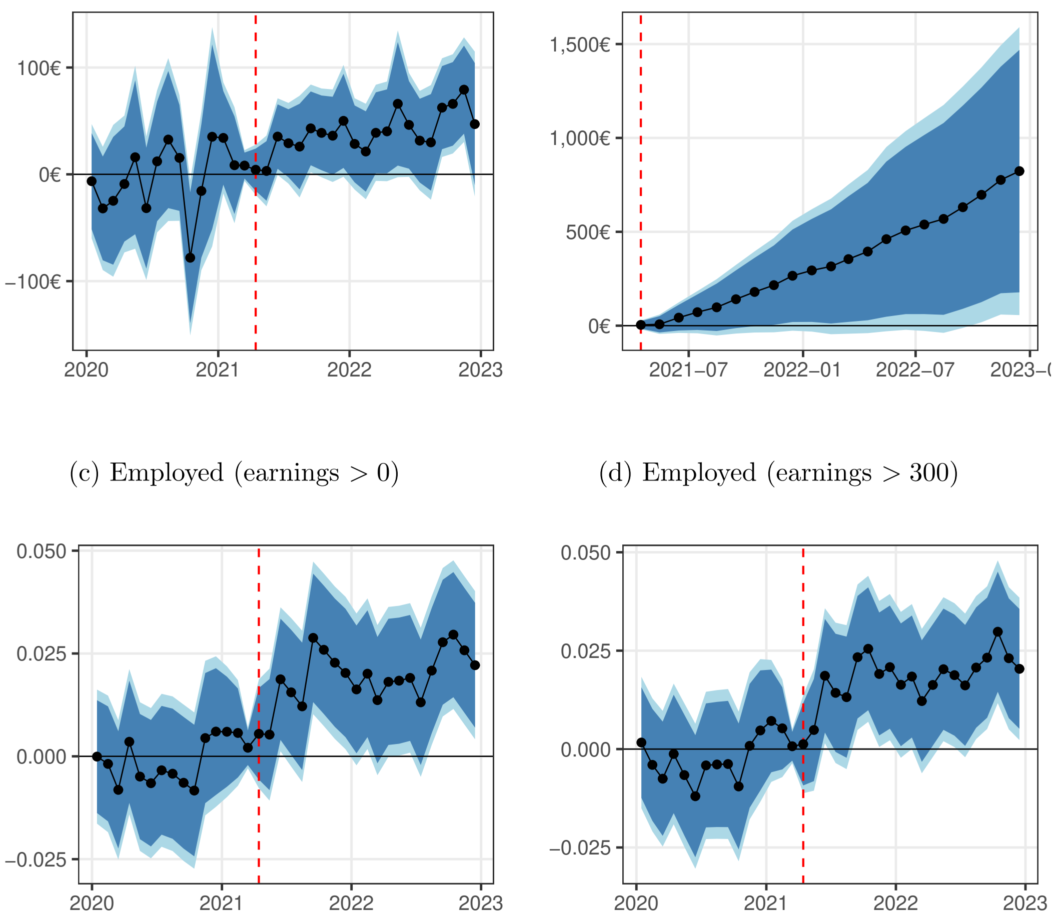


(d) UI benefit receipt (cumulative effects)



In Figure 9 we consider monthly labor earnings. In panel (a) We find no significant differences prior to the intervention except for one outlier. Post-treatment coefficients are all positive, with most months showing borderline statistical significance. Towards the end of 2022 the treatment effects are significant at the 5% level. In panel (b) we find that the treatment impact on cumulative earnings grows over time, again significant at the 10% level in most months. Towards the end of 2022, the treatment impact is significant at the 5% level and reaches a magnitude of around € 800. 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

Figure 9: Treatment impact on earnings and benefit receipt: individuals without employment in March-2021



(a) Labor earnings

(b) Labor earnings (cumulative effect)

(c) Employed (earnings > 0)

(d) Employed (earnings > 300)

periods (significant at the 5% level for most months). Employment is about 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). Also here we finding a significant increase in employment for those that received the information messages.

Summarizing, our results indicate that in the long-run the treatment led to approximately 60 additional hours worked and €800 higher labor earnings. In the appendix (Figures B2 and B3) we provide similar analyses for individuals that already worked a positive number of hours in March 2021.

Table 4: Outflow survey

	Share of Sample				Share of Invited			
	Control (N=4930)	Treatment (N=9882)	Diff.	p	Control (N=2399)	Treatment (N=4936)	Diff.	p
Invited to survey	0.487	0.499	-0.013	0.144				
Opened survey	0.144	0.163	-0.02	0.002	0.296	0.327	-0.031	0.007
Responded job found	0.112	0.128	-0.015	0.008	0.231	0.256	-0.025	0.022

The numbers for the control and treatment group in the rows below 'Share of Sample' are the number of observations relevant to the row (e.g. number of individuals invited to the survey) divided by the number of individuals in the full sample. The same holds for 'Share of Invited'.

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 proxy of job finding.[12] 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 4 provides a summary of the response to the survey. Of the 14,812 individuals in our non-Covid subsample, 7,335 received an invitation to fill out the outflow survey. The first row shows that while the share of treated individuals who received an invitation is slightly higher (0.499) than that of the control group (0.487), the difference is not statistically significant. In the last row we show that 11.2% of the control group individuals confirmed in the survey that they started a new job, while this is slightly larger for the treatment group (12.8%). 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 footnote 14 (but note that the difference is small, limiting the magnitude of potential selection bias).

Table 5 provides insights into what type of jobs people found. The table

[12] 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.

compares the occupation of the new job with the 'selection occupation'.[13] Each row shows the share of respondents that found employment in the same occupation as the occupation they were selected for. The difference between the rows is the occupational classification used, going from very fine grained (5-digit) in Row 1, to very broad (2-digit) in Row 4. We find that for 14-20% the new job is the exact same occupation as the occupation that we selected them for. Using broader classifications this share grows to more than 50% (when comparing only 2 digits). Regardless of the occupational classification, a larger share of treated individuals indicate that they found a job that is different from the one they were selected for. This difference is approximately 5 percentage points and statistically significant. Note that errors in the classification are likely to occur, which would lead us to underestimate the numbers in Table 5. 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.[14]

In summary, we find some evidence that employment (hours worked) 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. 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.

5.2.4 Treatment effect on survey responses

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

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

[14] As shown in Table 4, the response rate to the outflow survey was slightly larger in the treatment group. It is however straightforward to show that potential selectivity in the response rate cannot explain the occupational differences. If the response rate in the treatment group had equaled that of the control group (23.1% instead of 25.6%), the number of respondents would have been 1140. In the extreme case, all of the additional respondents (1263 - 1140 = 123) might have reported a different occupation for their new job. Under that assumption, the true statistic for "same 5-digit occupation" in Table 5 would have been 0.155, still considerably smaller than the control group value (0.20).

Table 5: Treatment effects: outflow to work

	Control (N=338)		Treatment (N=801)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Primary search occ (5-digit)	0.20	0.40	0.15	0.36	-0.05	0.05
Primary search occ (4-digit)	0.29	0.45	0.22	0.41	-0.07	0.01
Primary search occ (3-digit)	0.45	0.50	0.38	0.49	-0.07	0.03
Primary search occ (2-digit)	0.57	0.50	0.52	0.50	-0.06	0.09
Recommendation (5 digit)	0.12	0.32	0.14	0.35	0.02	0.32
Recommendation (4 digit)	0.25	0.43	0.29	0.45	0.04	0.17
Recommendation (3 digit)	0.25	0.43	0.25	0.44	0.00	0.86
Recommendation (2 digit)	0.28	0.45	0.30	0.46	0.01	0.69

The rows starting with '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). The rows starting with 'Recommendation' report the share of individuals who found work in one of the recommended occupations, *excluding* the primary search occupation (especially at high occupational coding levels these two often overlap).

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 6 we show regression estimates. The number of observations varies across columns, as we only include individuals who answered the respective questions in both the pre- and post-intervention surveys. We consider the following outcomes: (1) weekly time spent on exploring alternative occupations (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

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

	Dependent variable:					
	Time exploring	Applications	Interviews	Number of search occupations	Mean jobfinding score	Suggestions used in search set
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	0.252	−1.993	0.232	−0.106	0.041	0.072
	(0.532)	(1.455)	(0.257)	(0.151)	(0.100)	(0.049)
Post-period	−0.770	−0.877	0.012	−0.342*	0.222*	0.032
	(0.614)	(1.705)	(0.301)	(0.175)	(0.115)	(0.056)
Treatment*Post	−0.577	0.002	0.061	0.015	−0.162	−0.015
	(0.752)	(2.058)	(0.364)	(0.214)	(0.142)	(0.070)
Constant	5.354***	7.781***	0.554***	3.037***	3.765***	0.186***
	(0.434)	(1.206)	(0.213)	(0.124)	(0.081)	(0.040)
Observations	964	466	522	964	910	910

*p<0.1; **p<0.05; ***p<0.01. 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 4) and the probability of finding employment in the next two months (Column 5). Again, we find no statistically significant effects of the treatment on any of the belief measures.

These results are difficult to square with our finding that treated job seekers 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 30,000, 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 7: Difference-in-differences analysis survey outcomes: labor market beliefs

	Dependent variable:				
	Job offer rate per application primary	Job offer rate per application alternative	Expected stability primary	Expected stability alternative	Job finding probability
	(1)	(2)	(3)	(4)	(5)
Treatment group	−0.017	−0.015	−0.010	0.028	0.039
	(0.064)	(0.096)	(0.030)	(0.035)	(0.035)
Post-period	0.097	−0.107	−0.020	−0.007	0.081**
	(0.078)	(0.113)	(0.035)	(0.040)	(0.041)
Treatment*Post	−0.018	0.048	0.016	0.013	−0.008
	(0.094)	(0.136)	(0.043)	(0.049)	(0.050)
Constant	0.147***	0.282***	0.658***	0.669***	0.297***
	(0.053)	(0.081)	(0.025)	(0.028)	(0.029)
Observations	334	203	964	614	688

*p<0.1; **p<0.05; ***p<0.01. 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).

5.3 Remaining analyses

Various extensions of the analyses remain to be performed, as outlined in the pre-analysis plan that can be found in the AEA RCT registration. Firstly, there are a number of heterogeneity analyses to be done. We expect that job seekers' prior search strategy is an important determinant for treatment impact. For instance, we expect a more pronounced impact of providing information if job seekers initially search narrowly. In addition, we plan to explore heterogeneity by unemployment duration, expecting more willingness to consider alternatives among those who have been unemployed for a longer time. Both hypotheses are based on findings from Belot et al. (2019).

Second, we will investigate other job search activities that are collected administratively by the employment office. These include both measures of job search collected by case workers (applications and interviews) and records of online activities on the employment office's job search platform.

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. In addition we offer a motivational video aimed at overcoming behavioral hurdles associated with occupational transitions. Combining administrative data with pre- and post-intervention surveys to collect labour market beliefs, we measure how these interventions 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.

For unemployed job seekers looking for work in occupations with structurally poor labor market prospects, we find large effects of our information intervention. In the 20 months following the intervention, job seekers in these labor markets are about 2.5 percentage points more likely to be employed, work about 50 additional hours during this time, and earn €800 more. Based on survey data, we also find that these job seekers are more likely to end up in a different occupation than the one they were initially searching for work in. For job seekers in occupations for which demand rebounded after the Covid-19 pandemic, we do not find any impact of the intervention.

Our findings are promising since they indicate that individualized information stimulates unemployed job seekers to broaden their search to other occupations and that they are successful. The approach we use for providing information can be easily replicated in other settings. In addition, the actual intervention is low cost to implement, even on a very large scale. The underlying idea is that we make widely 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: 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 score (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 (Rank 1)	0.10^{***}	0.08^{***}	0.01
	(0.01)	(0.01)	(0.02)
Observations	165	165	165
R^2	0.27	0.33	0.45

Note: Table displays OLS regression at the suggestion-email level. Baseline category is rank 1. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A3: Comparison of composition of survey-respondents and rest of sample

	Non-survey (N=27340)		Survey (N=2789)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	p
Male	0.25	0.43	0.24	0.42	-0.01	0.17
Unemployment duration	32.25	28.00	31.43	28.71	-0.83	0.15
Remaining benefits (wks.)	49.96	29.53	61.03	29.48	11.07	0.00
Covid selection occ.	0.49	0.50	0.51	0.50	0.02	0.05
Selection Occupation:						
Activity counsellor	0.03	0.18	0.04	0.19	0.00	0.79
Archivist	0.01	0.10	0.01	0.09	0.00	0.26
Video and sound technician	0.01	0.10	0.00	0.07	-0.01	0.00
Janitor/Concierge	0.03	0.17	0.04	0.19	0.01	0.04
Animal caretaker	0.01	0.12	0.01	0.11	0.00	0.33
Printer	0.01	0.10	0.01	0.10	0.00	0.55
Graphic designer	0.03	0.16	0.03	0.16	0.00	0.74
Hotel receptionist	0.02	0.13	0.02	0.12	0.00	0.57
Hairdresser	0.02	0.14	0.01	0.12	-0.01	0.01
Bartender/waiter	0.16	0.37	0.14	0.35	-0.02	0.00
Canteen/Buffet employee	0.06	0.25	0.08	0.27	0.02	0.00
Office support staff	0.21	0.41	0.23	0.42	0.02	0.06
Primary school teaching assistant	0.02	0.15	0.02	0.12	-0.01	0.00
Event/conference organizer	0.03	0.16	0.02	0.13	-0.01	0.01
Producer (television/film)	0.01	0.09	0.01	0.09	0.00	0.80
Receptionist	0.16	0.37	0.19	0.40	0.03	0.00
Travel agent	0.02	0.12	0.02	0.13	0.00	0.70
Social worker	0.08	0.27	0.07	0.25	-0.01	0.02
Steward/stewardess	0.01	0.10	0.01	0.08	0.00	0.00
Taxi driver	0.04	0.21	0.05	0.22	0.01	0.15
Shop attendant household/leisure	0.01	0.12	0.01	0.11	0.00	0.73

Remaining benefits and unemployment duration are measured in March 2021.

Table A4: Survey responses about broader job search

	Mean	Std.Dev.	Min	Max
Search occupations suggested	0.23	0.49	0.00	3.00
Weekly hours exploring alternatives	5.61	5.95	0.00	20.00
Willingness to consider other occupations (1-5)	3.39	0.87	0.00	5.00
Confidence in working without experience (1-5)	3.76	0.80	0.00	5.00
Believes that skills are transferable (1-5)	3.76	0.80	0.00	5.00
Probability to expand search in two months	0.54	0.29	0.00	1.00
Observations	2,789			

Table A5: Balance table: administrative records

	Control (N=10004)		Treatment (N=20126)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	p
Unemployment duration	32.27	28.02	32.13	28.09	-0.14	0.68
Male	0.25	0.43	0.25	0.43	0.00	0.98
Covid selection occ.	0.49	0.50	0.49	0.50	0.00	0.77
Remaining benefit (wks.)	50.92	29.61	51.01	29.74	0.09	0.81
Selection Occupation:						
Activity counsellor	0.03	0.18	0.03	0.18	0.00	0.77
Archivist	0.01	0.10	0.01	0.10	0.00	0.71
Video and sound technician	0.01	0.10	0.01	0.10	0.00	0.80
Janitor/Concierge	0.03	0.17	0.03	0.17	0.00	0.74
Animal caretaker	0.01	0.12	0.01	0.12	0.00	0.95
Printer	0.01	0.10	0.01	0.10	0.00	0.96
Graphic designer	0.03	0.16	0.03	0.16	0.00	0.72
Hotel receptionist	0.02	0.13	0.02	0.13	0.00	1.00
Hairdresser	0.02	0.13	0.02	0.14	0.00	0.35
Bartender/waiter	0.16	0.37	0.16	0.37	0.00	0.96
Canteen/Buffet employee	0.07	0.25	0.07	0.25	0.00	1.00
Office support staff	0.21	0.41	0.21	0.41	0.00	0.88
Primary school teaching assistant	0.02	0.15	0.02	0.15	0.00	0.55
Event/conference organizer	0.02	0.16	0.02	0.15	0.00	0.88
Producer (television/film)	0.01	0.09	0.01	0.09	0.00	0.86
Receptionist	0.17	0.37	0.17	0.37	0.00	0.69
Travel agent	0.02	0.12	0.02	0.13	0.00	0.64
Social worker	0.08	0.27	0.08	0.27	0.00	0.97
Steward/stewardess	0.01	0.10	0.01	0.10	0.00	0.84
Taxi driver	0.05	0.21	0.04	0.21	0.00	0.44
Shop attendant household/leisure	0.01	0.12	0.01	0.12	0.00	0.85

Remaining benefits and unemployment duration are measured in March 2021.[Paul: Update when data arrives + add hours, earnings march-2021]

Table A6: Balance table: survey responses

	Control (N=931)		Treatment (N=1858)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	p
Unempl. duration	31.50	30.02	31.39	28.04	-0.11	0.93
Male	0.24	0.43	0.24	0.42	0.00	0.85
Job finding score sel. occ.	3.02	0.64	3.03	0.63	0.01	0.64
Covid selection occ.	0.52	0.50	0.50	0.50	-0.02	0.44
Time exploring alternatives	5.76	6.07	5.54	5.88	-0.22	0.35
Willingness work in new occ.	3.43	0.87	3.37	0.86	-0.06	0.11
My skills are transferable	3.77	0.81	3.76	0.79	-0.02	0.61
Prob. job in 2 months	0.42	0.30	0.42	0.30	0.00	0.86
Appl. needed (primary)	44.24	56.80	41.00	54.48	-3.24	0.24
Appl. needed (alt.)	43.98	56.36	40.82	54.45	-3.16	0.31
Salary previous job	2692.06	1168.23	2698.25	1197.17	6.19	0.90
Hours previous job	28.38	8.64	28.40	8.56	0.02	0.94
Expected wage (main occ.)	2617.08	827.09	2648.98	885.78	31.90	0.36
Reservation wage (main occ.)	2544.51	850.98	2572.46	891.78	27.94	0.43
Expected wage (alt. occ.)	2659.37	927.10	2717.81	1040.07	58.43	0.20
Reservation wage (alt. occ.)	2567.39	870.77	2611.17	963.83	43.78	0.30
Applications (main occ.)	3.17	6.90	3.13	5.76	-0.04	0.88
Job interviews (main occ.)	0.43	1.33	0.43	1.32	0.00	0.93
Applications (alt. occ.)	2.62	5.42	2.45	4.41	-0.18	0.47
Job interviews (alt. occ.)	0.37	1.03	0.37	1.04	0.00	0.92
Applications (other occ.)	2.83	6.43	2.46	4.71	-0.37	0.20
Job interviews (other occ.)	0.37	1.11	0.36	0.99	-0.01	0.91

Table A7: Balance table: administrative records non-covid occupations only

	Control (N=5074)		Treatment (N=10243)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	p
Male	0.27	0.44	0.27	0.44		0.90
Unemployment duration (wks.)	34.41	29.07	34.45	29.63	0.05	0.92
Remaining benefits (wks.)	49.78	28.94	49.83	29.00	0.05	0.92
Covid selection occ.						
Selection Occupation:						
Activity counsellor	0.07	0.25	0.07	0.25		0.81
Archivist	0.02	0.14	0.02	0.14		0.69
Video and sound technician	0.02	0.14	0.02	0.14		0.78
Janitor/Concierge	0.06	0.23	0.06	0.23		0.77
Animal caretaker	0.03	0.16	0.03	0.16		0.93
Printer	0.02	0.14	0.02	0.14		0.94
Graphic designer	0.05	0.23	0.05	0.22		0.68
Office support staff	0.42	0.49	0.42	0.49		0.99
Primary school teaching assistant	0.04	0.20	0.04	0.21		0.58
Event/conference organizer	0.05	0.22	0.05	0.21		0.84
Producer (television/film)	0.02	0.13	0.02	0.13		0.89
Social worker	0.16	0.37	0.16	0.36		0.90
Steward/stewardess	0.02	0.14	0.02	0.14		0.86
Shop attendant household/leisure	0.03	0.16	0.03	0.16		0.88

Remaining benefits and unemployment duration are measured in March 2021.

Table A8: Balance table: survey responses non-covid occupations only

	Control (N=447)		Treatment (N=921)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	p
Unempl. duration	34.84	32.72	33.27	29.55	-1.57	0.39
Male	0.28	0.45	0.27	0.44	-0.01	0.57
Job finding score sel. occ.	3.01	0.59	2.99	0.54	-0.01	0.69
Time exploring alternatives	5.58	5.97	5.61	5.93	0.02	0.95
Willingness work in new occ.	3.45	0.88	3.41	0.86	-0.04	0.44
My skills are transferable	3.88	0.81	3.83	0.80	-0.05	0.27
Prob. job in 2 months	0.40	0.31	0.39	0.29	-0.01	0.65
Appl. needed (primary)	51.69	61.44	42.73	54.77	-8.95	0.03
Appl. needed (alt.)	50.60	64.09	39.39	51.36	-11.21	0.02
Salary previous job	2988.66	1212.55	2991.31	1199.65	2.65	0.97
Hours previous job	29.37	8.49	29.32	8.16	-0.06	0.90
Expected wage (main occ.)	2903.57	900.01	2918.46	929.40	14.89	0.78
Reservation wage (main occ.)	2772.45	848.93	2811.36	907.74	38.91	0.45
Expected wage (alt. occ.)	2866.69	899.44	2923.22	1005.29	56.53	0.37
Reservation wage (alt. occ.)	2716.34	828.04	2832.96	969.60	116.62	0.05
Applications (main occ.)	3.40	8.35	3.15	6.63	-0.25	0.60
Job interviews (main occ.)	0.36	1.07	0.44	1.58	0.08	0.29
Applications (alt. occ.)	2.86	6.51	2.23	3.68	-0.64	0.11
Job interviews (alt. occ.)	0.34	0.96	0.39	1.11	0.05	0.48
Applications (other occ.)	2.45	5.13	2.36	4.75	-0.09	0.80
Job interviews (other occ.)	0.37	1.16	0.34	1.05	-0.03	0.74

Appendix B: Additional Figures

Figure B1: Comparing suggestions and initial search occupations

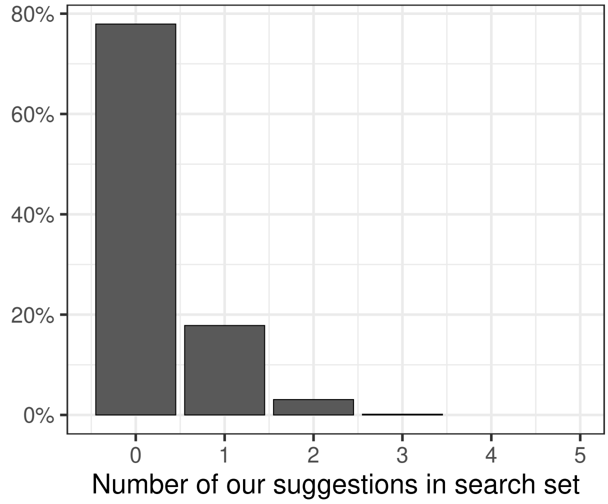
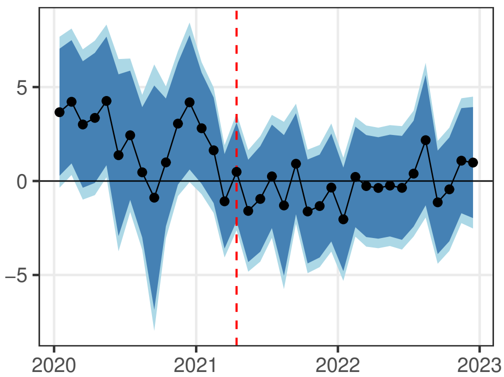
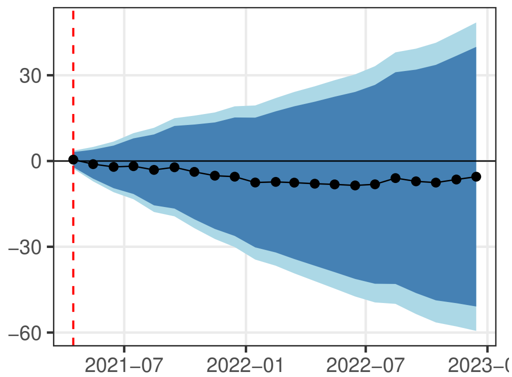


Figure B2: Treatment impact on hours worked and employment: individuals working positive hours in March-2021

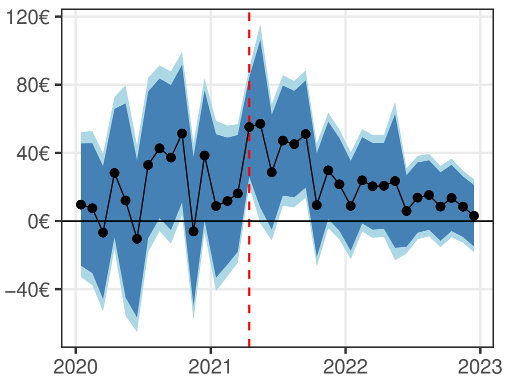
(a) Hours worked



(b) Hours worked (cumulative difference)



(c) UI benefit receipt



(d) UI benefit receipt (cumulative effects)

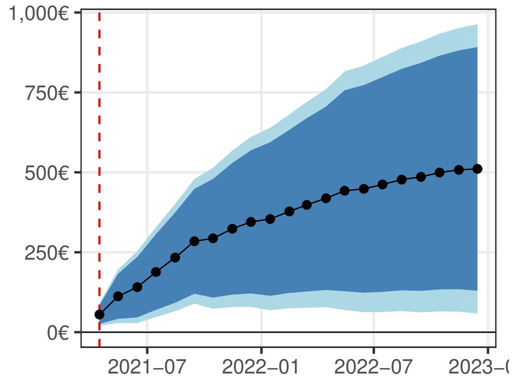
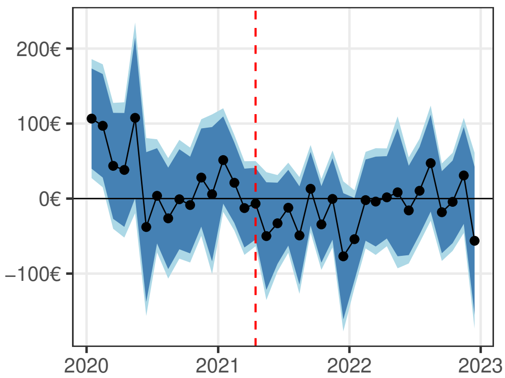
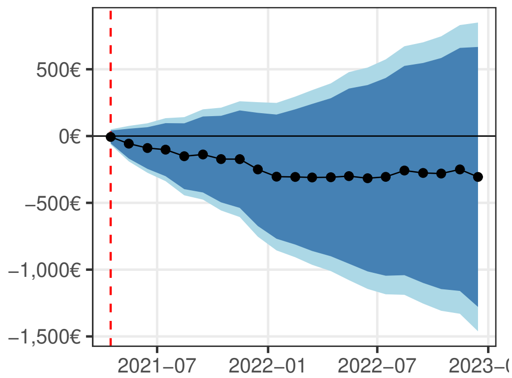


Figure B3: Treatment impact on earnings and benefit receipt: individuals working positive hours in March-2021

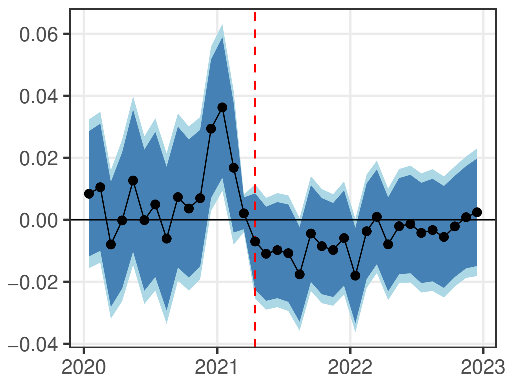
(a) Labor earnings



(b) Labor earnings (cumulative effect)



(c) Employed (earnings > 0)



(d) Employed (earnings > 300)