The Direct and Indirect Effects of Online Job Search Advice*

Steffen Altmann[†] **Anita M. Glenny**[‡]
Robert Mahlstedt[§] **Alexander Sebald**[¶]

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Abstract

We study how online job search advice affects the job search strategies and labor market outcomes of unemployed workers. In a large-scale field experiment, we provide job seekers with vacancy information and occupational recommendations on an online dashboard. A two-stage randomized design with regionally varying treatment intensities allows us to account for treatment spillovers. Our results show that online advice is highly effective when the share of treated workers is relatively low: in regions where less than 50% of job seekers are exposed to treatment, working hours and earnings of treated job seekers increase by 8.5–9.5% in the year after the intervention. At the same time, we find substantial negative spillovers on other treated job seekers for higher treatment intensities, resulting from increased competition between treated job seekers who apply for similar vacancies.

Keywords: Job Search, Unemployment, Information Frictions, Job Search Assistance, Online Advice, Occupational Recommendations, Public Policy, Field Experiments, Spillover Effects

JEL codes: J62, J64, J68, D83, C93

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[†]IZA Bonn and University of Copenhagen; altmann@iza.org

[‡]Aarhus University; glenny@econ.au.dk

[§]University of Copenhagen and IZA Bonn; robert.mahlstedt@econ.ku.dk

[¶]Copenhagen Business School; acs.eco@cbs.dk

1 Introduction

Information frictions are a pervasive feature of the job search process. Workers commonly lack information about earning possibilities in alternative jobs (Jäger *et al.* 2021), the rules and features of the tax and social benefit system (Chetty and Saez 2013, Altmann *et al.* 2022), the returns to occupational flexibility (Belot *et al.*, 2019), or their overall employment prospects (Spinnewijn, 2015; Mueller *et al.*, 2021; Mueller and Spinnewijn, 2022). To address these informational challenges and help unemployed workers back into employment, labor market policy rests on a key pillar—job search assistance and counseling. While job search assistance has, traditionally, been a core task of caseworkers, coaches, and counselors, recent years have seen an immense interest by public employment services and private providers in using digital tools for job search assistance (for an overview, see Kircher, 2022). Similar to other economic settings, digital advice bears two distinct promises in the context of job search. First, it enables policy makers to disseminate information at low marginal costs potentially yielding a large-scale reduction of search costs and information frictions. Second, it allows to provide tailored advice for different groups of workers, which may increase the value of the provided information substantially. While the benefits of digital assistance are rather clear-cut in settings with non-rival goods (see, e.g., Goldfarb and Tucker, 2019), the competitive nature of labor markets raises concerns that the positive direct effects of advice on the individuals who receive assistance have to be weighed against potentially negative indirect effects on other market participants (see Crépon *et al.*, 2013; Gautier *et al.*, 2018).

In this paper, we study the direct and indirect effects of online job search advice on the job search strategies and labor market outcomes of unemployed workers. We report results from a large-scale randomized controlled trial (RCT) that we conducted among the universe of unemployment benefit recipients in Denmark (N$\sim$92,000). In the experiment, we exogenously varied the content of a new digital dashboard that provides personalized information to job seekers on the central online platform of the Danish public employment agency. We focus on two distinct forms of online job search advice, which we compare against a control group that only receives generic information on features and functionalities of the online platform.[1] In a first treatment (the *vacancy information treatment*), we provide each job seeker with information about the number of available vacancies in occupations that fit their personal job search profile. In a second treatment, the *recommendation treatment*, job seekers receive referrals to suitable

[1]Our treatments were inspired by earlier evidence documenting substantial occupational mismatch (Şahin *et al.*, 2014; Herz and Van Rens, 2020; Patterson *et al.*, 2016), suggesting that learning about their occupation-specific employment prospect is an important driver of individuals' labor market success (see, e.g., Neal, 1999; Gibbons and Waldman, 1999; Gibbons *et al.*, 2005; Groes *et al.*, 2015; Papageorgiou, 2014) and showing that a broader occupational focus leads to more job interviews among unemployed workers (Belot *et al.*, 2019).

alternative occupations that might be a good fit for the job seeker, given her personal job search profile. These occupational recommendations were derived from data about successful recent labor market transitions of similar workers. A third group of job seekers, assigned to the *joint treatment*, receives both vacancy information and occupational recommendations.

Our setup combines four distinct features that make it ideally suited to study the effects of online job search advice. First, the dashboard is prominently placed on job seekers' main personal site on the online platform, which all unemployment benefit recipients in Denmark are required to visit at least once per week. Issues like selection to the web platform, user anonymity, and sample attrition that regularly complicate the analysis in online settings (see, e.g., Kudlyak *et al.*, 2013; Altmann *et al.*, 2019) are therefore less of a concern in our setup. Second, as participants are logged in on the platform, we can tailor the advice to job seekers' individual characteristics. In particular, unemployed workers in our setting are required to specify a personal job search profile consisting of the occupations in which they are searching for a job. The algorithm for occupational recommendations directly builds on this personal profile. Similarly, the vacancy information is continuously updated and tailored to job seekers' personal job search profile and their place of residence. A third key feature of our setup is that we can link the data from our experiment to comprehensive administrative data including information on registered job applications as well as detailed information on subsequent employment and earnings. Finally, our setup allows us study potential treatment spillovers and other indirect effects of online job search advice, building on a two-stage randomized trial design with regionally varying treatment intensities.

The different forms of job search advice provided through our intervention are expected to alleviate information frictions that job seekers face when allocating search effort across different occupations. The first part of our analysis focuses on changes in workers' job search strategies in response to the information provided on the dashboard. Specifically, we analyze individual-level data on job applications that unemployed workers have to register on the online platform. We document that job seekers indeed change their search strategies in response to the intervention. The precise ways in which they do so differ systematically across treatments. Job seekers who receive occupational referrals tend to follow the recommendations and apply more frequently to the suggested occupations. Conversely, among job seekers in the vacancy information treatment, we observe an increased focus on the 'core' occupations that were already stored in job seekers' personal job search profile before our intervention. This holds, both, compared to individuals in the recommendation treatment and the control group. For individuals in the joint treatment who receive both vacancy information and occupational recommendations, we observe no systematic change in the occupational breadth of applications, in line with the finding that the two types of information lead to countervailing changes in job seekers' application behavior. Finally, for all forms of online job search advice considered, we find that treated individuals apply, on average, to occupations with more favorable overall conditions—occupations that were initially characterized by a lower number of job seekers per vacancy—relative to the control group. Hence, the altered job search strategy has the potential to improve job seekers' reemployment prospects and corresponding labor market outcomes.

In the remaining parts of our empirical analysis, we investigate whether this is actually the case. When analyzing the labor market effects of our intervention, we account for potential treatment spillovers by considering heterogeneous effects across regions with exogenously varying treatment intensities. Our experiment, thus, allows us to provide a nuanced picture of the direct and indirect effects of online job search advice on treated and untreated job seekers. Providing advice may create different types of externalities as it encourages job seekers to reallocate their applications. This may change the competitive pressure between applicants in different occupations and thereby alter the overall effectiveness of job search advice. Our two-stage randomized design enables us to explore the relevance of such *indirect effects* of the intervention.

We follow the experimental population for a period of 12 months after the beginning of the intervention, by linking the data from our experiment to comprehensive register data on employment, working hours, and earnings. Without accounting for potential treatment spillovers, we find relatively small labor market effects of the different treatments. This picture, however, changes completely when we take into account the indirect effects of our intervention. Specifically, our findings show that online job search advice has substantial positive direct effects on job seekers' labor market performance, as long as the fraction of treated individuals is relatively low: when less than 50% of job seekers are exposed to treatment, both occupational recommendations and vacancy information increase labor earnings and overall working hours of treated job seekers by 8.5–9.5% in the year after the beginning of the intervention. Notably, our results suggest that the positive effects of providing vacancy information and occupational recommendations do not seem to 'add up' when being combined. While employment and earnings of those assigned to the joint treatment still lie significantly above the levels in the control group, point estimates are somewhat smaller than those for the recommendation and the vacancy information treatment.

Our data also demonstrate that online job search advice has substantial indirect effects on other unemployed workers. Most notably, we find strong negative effects of our intervention on other treated job seekers. In regions with high treatment intensities, where more than 75% of job seekers receive online advice, working hours and earnings of individuals who are assigned to one of the three treatment groups are at a level similar to that of the control group and lie significantly below the labor market outcomes of treated individuals in low-intensity regions. This implies that the positive direct effects of our treatments are fully offset when approaching a full roll-out of the intervention. Conversely, we find no evidence for negative spillovers on non-treated job seekers, as they have been documented for some traditional job search assistance programs (see, e.g., Blundell *et al.*, 2004; Crépon *et al.*, 2013; Gautier *et al.*, 2018; Cheung *et al.*, 2019). If anything, job seekers in the control group tend to benefit from a larger share of treated individuals. A further analysis of registered job applications suggests that the observed indirect effects are provoked by crowding out among treated job seekers who apply to similar occupations. In particular, our intervention affects the allocation of job applications such that treated job seekers in regions with high treatment intensities apply to occupations in which they face more competition from other treated individuals, while the opposite is true for job seekers assigned to the control group.

Our findings contribute to several strands of the literature. Most directly related is a nascent literature on online job search advice initiated by Belot *et al.* (2019) and further investigated in a number of contemporaneous studies by Belot *et al.* (2022a), Belot *et al.* (2022b) and Ben Dhia *et al.* (2022). In line with our results for the occupational recommendations treatment, these studies show that occupational referrals lead job seekers to broaden their consideration set, and that this may have positive effects on employment and earnings.[2] Our study provides a number of important new insights to this literature. First, by studying occupational recommendations as well as the provision of vacancy information, we investigate the effects of different forms of online job search advice. We show that simple vacancy information can increase employment and earnings by a similar magnitude as occupational recommendations.[3] This indicates that information frictions and, more generally, labor supply constraints could hamper job seekers' labor market integration (see also Alfonsi *et al.*, 2020; Abebe *et al.*, 2021; Caria *et al.*, 2022).

[2]Specifically, Belot *et al.* (2019) show that occupational recommendations lead unemployed workers to search for and apply to a broader set of occupations, which in turn tends to increase the number of job interviews. In subsequent studies, Belot *et al.* (2022b) show that occupational recommendations increase the likelihood of finding stable jobs among long-term unemployed job seekers and Belot *et al.* (2022a) provide preliminary evidence suggesting that occupational referrals may spur job finding and occupational transitions among workers who search in occupations with poor labor market prospects. Conversely, Ben Dhia *et al.* (2022) find no employment effects of an intervention that encourages job seekers to use a private online platform that provides personalized advice to job seekers. Somewhat more distantly related, van der Klaauw and Vethaak (2022) document that mandatory requirements to search more broadly may even decrease job finding.

[3]This relates to a number of studies documenting that workers often change their job search behavior in response to simple information such as media coverage of plant expansions (Skandalis, 2018), the age of job postings (Albrecht *et al.*, 2020) or the number of other applicants for a job posting (Gee, 2019; Bhole *et al.*, 2021).

Second, the dashboard through which we provide job search advice is directly embedded into the official online platform of the public employment agency. Hence, we study a setting in which a large and representative sample of job seekers is exposed to online job search advice over a period of several months, which may lead to stronger treatment responses compared to 'one-off' information interventions or encouragement designs. Third, and perhaps most importantly, thanks to our country-wide intervention with exogenously varying treatment intensities, we provide first evidence that the negative indirect effects of online job search advice can indeed be substantial.

In doing so, our results also contribute to a growing literature that documents spillover effects in various economic applications, including labor market policy (Lise *et al.*, 2004; Albrecht *et al.*, 2009; Lalive *et al.*, 2015), public employment programs (Muralidharan *et al.*, 2022), cash transfers (Angelucci and De Giorgi, 2009; Egger *et al.*, 2022), individuals' retirement plan decisions (Duflo and Saez, 2003), or firms' access to loans (Cai and Szeidl, 2022). In our context, the negative indirect effects on other individuals receiving similar advice turn out to be particularly pronounced. It appears likely that this is a fundamental problem associated with the provision of tailored job search advice, as job seekers with similar profiles also receive similar information. Given the rising interest in algorithmic recommendations (see Horton, 2017; Kircher, 2022), our study provides a cautionary tale that the scaling of personalized advice may crucially affect its effectiveness (see also Muralidharan and Niehaus, 2017; Al-Ubaydli *et al.*, 2017, 2019, for general overviews). Therefore, it appears important that researchers and policy-makers account for possible spillover effects when designing tailored instruments to support unemployed workers in the job search process.

Bearing these challenges in mind, our results can also provide guidance on how to design online advice systems that have direct benefits for some job seekers, while limiting negative externalities for others. Specifically, when analyzing heterogeneous treatment effects, we find that occupational recommendations primarily improve the labor market outcomes of job seekers who initially searched in occupations with relatively poor labor market prospects. Conversely, the provision of vacancy information is more effective for job seekers who targeted occupations characterized by high labor-market tightness before the intervention. Against this backdrop, it seems promising to provide tailored advice to those subgroups of workers who benefit most strongly from a particular form of advice, while keeping the overall scale of the corresponding program limited.

Finally, our study enhances our understanding of the mechanics and implications of job search assistance, more generally. Numerous studies examined the effects of job search assistance and monitoring programs (see, e.g., Card *et al.*, 2010, 2017, for an overview), caseworker counseling (Behaghel *et al.*, 2014; Schiprowski, 2020), and information provision (Crépon *et al.*, 2018; Altmann *et al.*, 2018, 2022; Benghalem *et al.*, 2021) on the labor market prospects of unemployed workers. However, due to the absence of more informative data, evidence with respect to the underlying mechanisms behind the observed labor market effects is often missing. By combining a state-of-the-art experimental design with detailed administrative data and data on the job search process, our analysis can disentangle the direct and indirect effects of different forms of job search advice and investigate consequences for individual job search strategies and subsequent labor market outcomes.

The paper proceeds as follows. In the next section, we present the design of our randomized controlled trial. In Section 3, we discuss the potential effects of online job search advice through the lens of an occupational job search model. Sections 4 and 5 present the empirical results on how our intervention affects job seekers' application behavior and labor market outcomes, respectively. Section 6 concludes.

2 Study Design

In our randomized controlled trial, we aim at improving job seekers' understanding of their labor prospects in different occupations. To that end, we rely on a digital dashboard, which is embedded in the official online platform of the Danish public employment service (*jobnet.dk*), and which allows us to exogenously vary the information provided to individual job seekers. In what follows, we first describe the content and features of the dashboard, before explaining the experimental design in more detail.

2.1 The dashboard

The dashboard is embedded in job seekers' *main personal page* on jobnet.dk (i.e. the landing page that job seekers access after logging in on the online platform). Figure A.1 in the appendix illustrates a job seeker's main personal page, where the dashboard is displayed in the top middle part of the screen (see red box marked with (1)). Thanks to the dashboard's prominent position and the high usage of the platform—all UI benefit recipients in Denmark are required to log in on the platform at least once per week—it provides an ideal setting to study the effects of online job search advice. On the one hand, the dashboard allows to exogenously vary the information provided to job seekers in a natural manner, by simply varying which dashes are displayed to a particular job seeker. On the other hand, the information provided through the dashboard can be tailored towards a job seeker's personal situation. Specifically, the dashboard relies on an individual's *personal job search profile*, which all job seekers are required to specify when registering as unemployed with the public employment service. The job search profile includes a list of occupations in which the individual is interested to work in. Each job seeker chooses from about 1,020 potential occupations that are defined based on a Danish version of the international occupation classification system ISCO. Building on these profiles, the dashboard provides job seekers with tailored vacancy information and occupational recommendations through different information cards, which we describe in the following.

Vacancy information: The first information card informs job seekers about the overall number of vacancies currently available for the set of occupations stored in their personal profile (see Panel A of Figure A.2 in the appendix). The information relates to posted vacancies in a radius of 50 km around the individual's zip code of residence. It is updated on a daily basis, using information about all vacancies available in the vacancy database of the jobnet.dk platform, which covers more than 90% of all vacancies listed in Denmark. The vacancy information is presented together with a link to the subpage of the online platform, where job seekers can check and potentially amend their personal job search profile.

Occupational recommendations: The second information card, displayed in Panel B of Figure A.2, provides job seekers with recommendations for alternative occupations related to those stored in their personal job search profile. Each time a job seeker logs in on the online portal, one of the occupations stored in her personal profile is randomly selected. Based on this selected occupation, the individual receives suggestions for up to three alternative occupations. In the spirit of Belot *et al.* (2019), we derived recommendations from data about successful recent labor market transitions, expecting that this is informative for current job seekers, who may otherwise lack information about suitable alternative occupations. Specifically, we examined register data containing the universe of occupational transitions (unemployment-to-job transitions) in Denmark in the period 2013-2016. While workers frequently found employment in their previous occupation, others switched to a different occupation than the one they held before becoming unemployed. For each occupation, we counted the number of these occupational transitions and created a list with the five most common transitions (i.e., the most popular alternative occupations for each 'source' occupation).[4] The information card displays at most

[4]In particular, we considered occupational transitions of unemployed workers who received unemployment benefits for at least four weeks before they started a new job. Transitions are identified based on a six-digit ISCO code. Moreover, we enriched the data on occupational transitions with (1) information on the number of current vacancies for each occupation and (2) an additional measure of educational overlap between occupations. Thereby, we ensured that we do not recommend occupations that are not available to the job seeker due to a lack of vacancies or educational barriers.

three out of the five possible alternative occupations, given that these alternative occupations are not already stored in the job seeker's personal job search profile. Job seekers can directly access a list of all posted vacancies related to the recommended occupations by clicking on the recommended alternative occupation. Analogous to the vacancy information dash, job seekers can also click on a link to access and potentially alter their personal job search profile.

Generic information: Besides the two dashes containing tailored, occupation-specific information, the dashboard also features two generic information cards that do not provide any personalized information. One card (see Panel C of Figure A.2) links to a video that provides information about some general features and functionalities of the online platform. The other card (see Panel D of Figure A.2) provides a link to the subpage of the online platform on which job seekers can alter their personal job search profile. As described in more detail in Section 2.2, the two generic information cards are presented to individuals who are assigned to the control group in our experiment. Moreover, the generic cards also serve as a place holder to "fill up" the dashboard for job seekers in some of the other treatment arms of our experiment (see details below).

2.2 Randomized controlled trial

To study the causal effects of online job search advice, we exogenously varied the information cards to which an individual is exposed. The dashboard of each job seeker in the experimental sample contains two out of the four information cards and the individual's treatment status determines which cards are shown.

Table 1: Information cards displayed for treatment groups

Treatment group	**First card**	**Second card**
Control group	Video (C)	Search profile (D)
Recommendation treatment	Occupational recommendation (B)	Video (C)
Vacancy treatment	Vacancy information (A)	Video (C)
Joint treatment	Vacancy information (A)	Occupational recommendation (B)

For individuals assigned to the control group, the dashboard displays the two generic information cards (C) and (D) regarding features and functionalities of the online portal. As these cards only provide basic information that would be straightforward to obtain in absence of the dashboard, we expect them to have only very limited influence on job seekers' behavior. In addition, we randomly assigned job seekers to three treatment groups, which allows us to identify the causal effects of occupational recommendations, vacancy information, and their combined effect. Job seekers assigned to the *recommendation treatment* are exposed to the card containing occupational recommendations (B) and the generic video card (C). Job seekers assigned to the *vacancy treatment* receive information about the number of available vacancies in occupations stored in the job seeker's personal job search profile (A) and the generic video card (C). Finally, unemployed assigned to the third treatment, also denoted as *joint treatment*, are exposed to both vacancy information (A) and occupational recommendations (B).

2.3 Treatment assignment

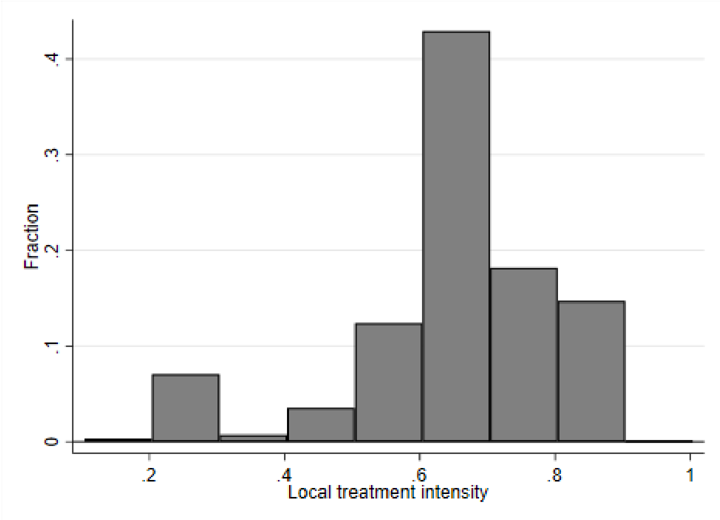
To study the importance of treatment spillovers, we implemented a two-stage randomized trial design, in which we varied treatment assignment at the individual and regional level (see also Crépon *et al.*, 2013; Baird *et al.*, 2018). In a first stage, we assigned all 98 municipalities in Denmark to one of three groups, which differ with respect to the shares of treated and non-treated individuals. In a second stage, we assigned each unemployed job seeker to the four treatment arms described in Section 2.2, based on the treatment weights in the job seeker's place of residence.

Table 2: Summary of the two-stage randomized trial design

		Treatment weights				
Assignment group	**No. of municipalities**	**Control group**	**Recom. treatment**	**Vacancy treatment**	**Joint treatment**	**No. of individuals**
Super control	10	100%	0%	0%	0%	10,100
60% assignment	44	40%	20%	20%	20%	45,232
90% assignment	44	10%	30%	30%	30%	36,766
Overall	98	32.5%	22.5%	22.5%	22.5%	92,098

In ten municipalities, all unemployed workers were assigned to the control group, while in all other municipalities, unemployed workers were randomly allocated to either the control group or to one of the three treatment groups (recommendation treatment, vacancy treatment, or joint treatment). In particular, in 44 municipalities, job seekers were assigned to the control group with a probability of 40% and they were assigned to one of the three information treatments with a probability of 20% each. In the remaining 44 municipalities, job seekers were assigned to each of the three treatments with probability 30%, whereas the individual probability of being assigned to the control group was 10%. This procedure, summarized in Table 2 and Figure A.3 in the appendix, ensures that the assignment of individuals to the four treatment groups is random within a municipality. Moreover, to ensure that municipalities are comparable across the three groups with different assignment probabilities, our first-stage assignment of municipalities rests on a stratified randomization based on an index that accounts for various characteristics of the labor markets in different municipalities, such as the local unemployment rate, labor market tightness, and the distribution of education and age in the local population.

Figure 1: Distribution of local treatment intensity



Note: Depicted is the local treatment intensity as the share of treated individuals (in all three treatment arms) among all job seekers within a regional area including the municipality of the individual's place of residence and all bordering municipalities. The mean (median) of the distribution is 0.66 (0.64) and the standard deviation is 0.15.

In our empirical analysis in Section 5, we exploit this heterogeneity with respect to the assignment probabilities to construct a continuous measure of treatment intensity that proxies the share of treated individuals searching for a job within the same geographical area. The continuous measure accounts for the fact that job seekers do not necessarily limit their search activities to their own municipality. Hence, for each of the 98 municipalities, we define the local treatment intensity TI_j by calculating the fraction of treated individuals (including all three treatment groups) within the job seeker's own municipality and all bordering municipalities. As shown in Figure 1, our two-stage randomization procedure creates substantial variation with respect to the share of treated individuals within a geographical area. While about 43% of the experimental population are exposed to a treatment intensity between 60% and 70%, treatment intensities vary between 10% and 91%. Hence, our empirical analysis of spillover effects can rely on data from local labor markets where job seekers have very little exposure to other treated individuals as well as markets with an almost full roll-out of the intervention.

2.4 Procedures, data, and sample statistics

All individuals who were registered as unemployed and received UI benefits on March 17, 2019 were randomly assigned to one of the four treatment arms, according to the assignment probabilities depicted in Table 2. In total, our sample comprises 92,098 individuals. Once job seekers were assigned to a treatment group, they are exposed to the same information cards each time they log in on the online platform. This is also the case when they found a job and re-enter unemployment at a later point in time.

To examine the effects of our intervention, we rely on a unique combination of different data sources, which can be linked at the individual level. First, we exploit comprehensive register data administered by Statistics Denmark that allow us to obtain highly reliable information on employment and earnings for all participants in our experiment over a period of 12 months after the start of the intervention. Notably, the first Covid-19 related lockdown in Denmark started on March 13, 2020, implying that all results reported below should not be affected by labor market disruptions related to the Covid-19 pandemic. The administrative data also provide us with detailed information on socio-demographic background characteristics obtained from population registers and benefit payments. Second, we also use information about job seekers' personal job search profiles and vacancy information from the job search platform of the online portal. This allows us to trace the exact information job seekers were exposed to during the intervention. Finally, we use data on job applications registered by job seekers on the online platform to document their job search activities (see Fluchtmann *et al.*, 2019). Most importantly, job applications are registered including an occupational identifier such that we can examine how the intervention affects individuals' job search strategies in terms of the targeted occupations.

Table 3 provides an overview of participants' background characteristics, separated by treatment status. The job seekers in our experiment are on average 40 years old, about 53% of participants are female, 35% are married or cohabiting, and 36% have a university degree. The average participant has been unemployed for about six months, had an average gross monthly labor income of roughly DKK 20,000 (approx. € 2,680), and worked on average 22 hours per week during the past three years (including periods of non-employment). While we observe only minor differences in background characteristics across treatments, a few of the balancing tests reported in the rightmost column of the table turn out to be statistically significant. To address these small differences between treatment arms, we condition on a rich set of covariates in our empirical analysis. We further discuss the validity of our empirical approach, especially the exogeneity of the local treatment intensity, in Section 5.

3 Theoretical Framework

Before we present the results of our RCT, we discuss the potential effects of online job search advice in a simple partial-equilibrium occupational job search model. In the spirit of, for in-

Table 3: Summary statistics and balancing tests

	Mean values by treatment status				Balancing stat.
	Control group	Recom. treatment	Vacancy treatment	Joint treatment	$P-$values
No. of observations	31,966	19,990	20,225	19,917	
Educational level					
Less than high school	0.190	0.190	0.190	0.193	0.797
High school	0.414	0.418	0.421	0.419	0.840
Bachelor degree (or equiv.)	0.267	0.263	0.258	0.260	0.615
Master degree (or equiv.)	0.098	0.099	0.100	0.098	0.842
Male	0.474	0.462	0.477	0.471	0.032
Age					
18 - 25 years	0.113	0.110	0.111	0.112	0.860
26 - 35 years	0.336	0.343	0.330	0.329	0.007
36 - 45 years	0.189	0.186	0.193	0.191	0.307
46 - 55 years	0.192	0.187	0.192	0.190	0.770
55 - 65 years	0.169	0.175	0.174	0.178	0.549
Married or cohabiting	0.558	0.553	0.551	0.544	0.134
Any children	0.365	0.371	0.374	0.375	0.621
Migration background	0.225	0.232	0.231	0.233	0.845
Elapsed benefit duration (in days)	173.2	171.3	173.2	171.1	0.694
Avg. monthly labor earnings (in DKK)					
in last year	18,286	18,510	18,505	18,705	0.604
in last three years	19,500	19,667	19,854	19,909	0.181
Avg. weekly working hours					
in last year	18.89	19.02	19.12	19.20	0.437
in last three years	22.09	22.15	22.34	22.394	0.096
Previous occupation before unemployment					
Managerial position	0.019	0.019	0.020	0.019	0.850
Professional position	0.152	0.153	0.152	0.152	0.976
Technicians and associated position	0.063	0.061	0.061	0.067	0.063
Clerical support worker	0.092	0.100	0.094	0.093	0.066
Service sales worker	0.201	0.202	0.195	0.202	0.062
Agricultural worker	0.006	0.006	0.007	0.006	0.750
Craft worker	0.057	0.053	0.057	0.054	0.289
Plant machine operator	0.048	0.050	0.051	0.053	0.463
Elementary occupation	0.153	0.148	0.152	0.150	0.685

Note: Percentage shares unless indicated otherwise. $P-$values are based on F-tests for joint significance of treatment coefficients in separate regressions of each of the characteristics on dummies for the different treatment conditions.

stance, Belot *et al.* (2019) and Kircher (2022), job seekers can direct their search effort towards different occupations, while they face uncertainty about the returns to their search effort in terms of their personal chances of finding employment in the various possible occupations.

3.1 Occupational job search model

While individuals are unemployed, they receive a flow of benefits, b, and they decide how to allocate their total search effort, $s \geq 0$, across K different occupations. The various occupations differ regarding the rate at which job seekers can generate job offers, $\lambda_k(s_k)$, where s_k indicates the effort allocated to a specific occupation k. At the same time, job seekers are uncertain about their job prospects within the various occupations. For a given effort level, s_k, allocated to occupation k, job seekers hold a subjective belief, $\widehat{\lambda}_k(s_k)$, regarding the occupation-specific job offer arrival rate, which might differ from the true rate at which job seekers can generate job offers, $\lambda_k(s_k)$. The effort costs, $\gamma(s)$, depend on their total effort level across all occupations, with $\gamma'(s) > 0$ and $\gamma''(s) > 0$. For illustrative purposes, we assume that all jobs offer the same wage w.

Individuals maximize their perceived present value of income over an infinite horizon with discount rate ρ, whereas U denotes the value of being unemployed and V the value of being employed:

$$\rho U = \max_{s_1,\dots,s_K} \left[b - \gamma(s) + \sum_{k=1}^{K} \left\{ \widehat{\lambda}_k(s_k)(V(w) - U) \right\} \right] \tag{1}$$

The optimal search strategy is characterized by the effort vector $s^* = (s_1^*, ..., s_K^*)$, which trades-off effort costs and the marginal returns to effort in the different occupations. In our setting, the allocation of search effort across occupations depends on the job seeker's belief about the relative marginal returns to effort $\widehat{\lambda}'_k$ across the various occupations.

3.2 Potential effects of job search advice on job seekers' behavior

To understand the potential effects of occupational recommendations and vacancy information, suppose that, for each job seeker, there exist two classes of occupations. For 'core' occupations, job seekers' subjective belief about the job offer arrival rate is sufficiently high such that they store the corresponding occupations in their personal job search profile (before the start of the intervention). Job seekers' subjective belief regarding the job offer arrival rate in other 'non-core' occupations is lower such that they do not store these occupations in their search profile. The distinction between core and non-core occupations is crucial to understand the behavioral consequences of occupational recommendations and vacancy information. At the same time, one should note that job seekers may send their actual job applications either to their core occupations or to both core and non-core occupations.[5]

Occupational recommendations: As highlighted by Belot *et al.* (2019), such a framework can predict the impact of occupational recommendations on the search behavior of unemployed workers. Intuitively, receiving a recommendation regarding an occupation k should increase the individual belief about the returns to effort in the recommended occupation. Given that our algorithm only recommends 'non-core' occupations that are not stored in the initial job search profile, receiving a recommendation should make the recommended occupations relatively more attractive and thus encourage individuals to exert relatively more effort searching for a job

[5] Empirically, we observe that job seekers send about 53% of their applications to core occupations stored in their personal job search profile.

in recommended non-core occupations. In addition, as indicated by the convex cost function, job seekers' resources (i.e., the time and effort that they can exert for job search) are limited. Therefore, one would expect that searching more intensively for jobs in non-core occupations comes at the cost of reduced search activities in other occupations such as the core occupations they initially stored in their personal job search profile.

Whether such an altered search strategy improves labor market outcomes depends on the actual prospects in the various occupations, $\lambda_k(s_k)$. For example, occupational recommendations might be more effective and thus lead to better labor market outcomes for job seekers who initially consider occupations with relatively bad employment prospects (e.g., occupations with few vacancies or low labor-market tightness) compared to the occupations recommended by our algorithm.

Vacancy information: In contrast to occupational recommendations, receiving information about the number of vacancies in occupations that are already stored in job seekers' personal job search profile should affect their belief about the employment prospects in these core occupations.

Behavioral reactions to this information will hinge on the job seekers' prior expectations. Job seekers may be positively surprised by the number of vacancies in their core occupations and may assume that 'positive news' regarding the number of vacancies in their core occupations means that the returns to effort are larger than expected (e.g., if some or all of the core occupations are in particularly high demand). In this case, they would shift their search effort from non-core to core occupations. If this effect is strong enough, individuals may reduce the occupational broadness of their search activities in response to positive vacancy information. Conversely, one may expect that job seekers who receive a negative signal about their core occupations shift their search activities towards non-core occupations.

Again, the labor market effects of receiving vacancy information are not clear-cut. They depend on whether individuals perceive the vacancy information as a negative or positive signal and on the actual labor market prospects in the job seekers' core occupations. For example, if the vacancy information is a positive surprise to individuals and labor market prospects in core occupations are better than expected, focusing search activities on core occupations should entail positive labor market effects.

3.3 Externalities of job search advice

The partial-equilibrium model presented above assumes that if some workers increase their search effort in a certain occupation, the extra labor supply is absorbed by the creation of additional employment. In reality, however, job creation may not fully adjust such that changes to an individual's search behavior have externalities on other job seekers. To illustrate this, we can adjust the framework above by assuming that the rate at which an individual can attract job offers in occupation k does not only depend on her own effort choice, s_k, but also on the occupation-specific labor market tightness, θ_k:

$$\lambda_k(\theta_k, s_k) \quad \text{with} \quad \theta_k = v_k/u_k. \tag{2}$$

Here, v_k denotes the total number of open vacancies in occupation k and u_k is the total effort exercised by the unemployed searching for jobs in occupation k (see, e.g., Michaillat, 2012; Crépon *et al.*, 2013, for more formal illustrations). For a given effort level s_k, the probability that an unemployed worker finds a job in occupation k is both increasing and concave in θ_k. Providing occupation-specific job search advice to some job seekers may create different types of externalities by changing the effort allocation of job seekers across different occupations and thereby the occupation-specific labor market tightness.

First of all, it is often highlighted by the existing literature that treated job seekers may benefit at the expense of individuals who do not receive the same treatment (see, e.g., Gautier *et al.*, 2018; Cheung *et al.*, 2019). As outlined above, both occupational recommendations and vacancy information may encourage job seekers to exert more effort searching for jobs in certain occupations. This implies that the labor market tightness decreases in occupations that become more popular among treated individuals. This lowers the job finding prospects of those who would search for jobs in these occupations in absence of the intervention. At the same time, we expect treated job seekers to reduce their search activities in other occupations, which may improve the reemployment prospects of those searching for jobs in occupations that become relatively less popular among treated individuals. Whether positive or negative spillovers are more important for individuals in the control group ultimately depends on the distribution of their search effort across occupations. For instance, one would expect negative spillovers to be particularly important if many non-treated individuals search in occupations that are highlighted by the intervention and vice versa.

Secondly, there could be also treatment spillovers on treated individuals, for instance, if they do not take into account that others receive similar information (see e.g. Ferracci *et al.*, 2014). In our setting, the advice that job seekers receive depends on their personal job search profile. This implies that treated individuals with similar profiles also receive the same kind of advice. This, in turn, may reduce the labor market tightness in certain occupations that are frequently highlighted. As a consequence, there could be crowding out among treated job seekers applying for similar vacancies, which eventually reduces the effectiveness of search advice when the fraction of treated individuals increases.

4 How Does the Intervention Alter Job Search?

In a first step of our empirical analysis, we examine whether occupational recommendations and vacancy information affect job seekers' search behavior as suggested by our theoretical discussion in Section 3.2. We exploit individual-level data on job applications registered in the online portal of the public employment service. The data provide an ideal basis to study the effects of the intervention because registered applications include an identifier for the occupation associated with the corresponding vacancy, which can be directly compared to the occupations stored in the job seekers' search profile, respectively the one's recommended by our algorithm. Moreover, previous evidence by Fluchtmann *et al.* (2019) suggests that the data are informative on how job seekers allocate their applications across occupations.[6]

In what follows, we present treatment effects on search outcomes measured within a four-week period after the beginning of the intervention. During this time period, about 93% of the experimental population had registered at least one application. We estimate regressions of the following form:

$$Y_i = \alpha_1 D_i + \beta_1 X_i + \varepsilon_i. \tag{3}$$

As outcome variables, Y_i, we consider (1) the share of job applications in core occupations, which were stored in the individual's personal job search profile at the beginning of the intervention, (2) the share of job applications in occupations recommended by our algorithm, (3) the number of applications in distinct occupations (normalized by the total number of applications) and (4) the average labor market tightness in the occupations applied to. D_i indicates the individual treatment status (i.e., dummy variables for the recommendation, vacancy and joint treatments, respectively) and X_i is a vector of pre-intervention control variables including age, gender, education, labor market histories, unemployment duration and dummies for the job seeker's place of residence (98 municipalities). Standard errors are clustered at the level of municipalities.

The estimation results, which are summarized in Table 4, show that online job search advice alters individuals' job search behavior and that job seekers' responses to the intervention systematically depends on the type of advice they received.

[6] It should be noted that UI benefit recipients are required to document a minimum number of approximately two applications per week (the exact requirement depends on the specific UI fund who is responsible for UI benefit payments). This means that the registered applications may not capture all search activities and it is, thus, difficult to draw conclusions about the overall search effort.

Table 4: Job search behavior: treatment differences in registered job applications

Dependent variable	Registered job applications within four weeks: Fraction recom. occupations[(a)]	Fraction core occupations[(b)]	Fraction distinct occupations[(c)]	Avg. labor market tightness[(d)]
	(1)	(2)	(3)	(4)
Treatment status (ref. control group)				
Recommendation treatment	0.0063**	-0.0085***	0.0035	0.0114***
	(0.0030)	(0.0033)	(0.0023)	(0.0039)
Vacancy treatment	-0.0015	0.0082**	-0.0062***	0.0101***
	(0.0030)	(0.0033)	(0.0023)	(0.0039)
Joint treatment	0.0038	0.0052	-0.0034	0.0100**
	(0.0030)	(0.0033)	(0.0023)	(0.0039)
No. of observations	82,957	82,957	82,957	82,957
Mean value controls group	0.265	0.526	0.500	0.136
Control variables	Yes	Yes	Yes	Yes

Note: The table reports treatment differences in search outcomes measured based on job applications registered in the online portal of the public employment service within the first four weeks following the start of the experiment. Standard errors are reported in parenthesis and are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level.
[(a)] Share of registered job applications sent to non-core occupations that were or would have been recommended by the algorithm.
[(b)] Share of registered job applications sent to core occupations, which were already stored in the job seeker's search profile in the week before the start of the intervention.
[(c)] Number of registered job applications sent to distinct occupations normalized by the total number of registered applications.
[(d)] Average labor market tightness across all occupations applied to. The labor market tightness is calculated based on the number of job seekers who stored the corresponding occupation in their search profile relative to the number of available vacancies measured at the start of the intervention.

Recommendation treatment: As suggested by the estimates in column (1) of Table 4 job seekers tend to follow the occupational recommendations that they received. Relative to the control group, individuals in the recommendation treatment send a larger fraction of their job applications to occupations that were recommended on their dashboard (+2.4%; $p = 0.036$). At the same time, they reduce the share of applications sent to their core occupations, which were stored in their personal job search profile at the beginning of the intervention, by about 1.6% ($p = 0.010$; see column 2). These effects are in line with the theoretical idea that occupational recommendations have a positive effect on job seekers' beliefs regarding the returns to search effort in the recommended occupations.[7] Similar to Belot *et al.* (2019), occupational recommendations seem to encourage job seekers to broaden the set of occupations that they consider. Moreover, the estimates shown in column (4) also indicate that—in absence of treatment externalities—the altered search strategy has the potential to improve job seekers' reemployment prospects. This is because treated individuals tend to focus their search activities on occupations with a higher labor market tightness, i.e., occupations with a higher number of

[7] One interpretation of these findings is that job seekers shift their search effort from core to recommended occupations in response to the occupational referrals. Alternatively, it could also be the case that treated individuals send additional job applications to recommended occupations without reducing the absolute number of applications in their core occupations.

vacancies per job seeker. On average, individuals assigned to the recommendation treatment apply to occupations with an average labor market tightness—measured at the start of the intervention—that is 8.4% ($p = 0.004$) higher than for the control group.[8]

Vacancy treatment: In contrast to occupational recommendations, the vacancy treatment increases the fraction of applications sent to job seekers' core occupations, which are stored in their initial search profile (see column 2). Relative to the control group, we find an increase of about 1.6% ($p = 0.013$). Moreover, the vacancy treatment also reduces the fraction of applications sent to distinct occupations by 1.2% ($p = 0.007$; see column 3). These effects are consistent with the idea that, on average, job seekers interpret the vacancy information as positive news about the returns to search in their core occupations that are initially stored in their job search profile, which encourages them to focus their search activities on these occupations. Interestingly, as shown in column (4), the altered search strategy is also accompanied by an increase in the average labor market tightness in the occupations to which job seekers apply (7.4%; $p = 0.005$). The effect is of similar magnitude as the corresponding effect of the recommendation treatment.

Joint treatment: Finally, when considering the portfolio of applications for job seekers in the joint treatment, differences with respect to the control group are less pronounced than for the recommendation and the vacancy treatment, respectively. This might not be too surprising, given that the joint treatment combines occupational recommendations and vacancy information, which seem to provoke opposite behavioral responses of job seekers (i.e., a broadening of the job search strategy in response to occupational recommendations, and a narrowing down in response to vacancy information). Nevertheless, we also observe that individuals in the joint treatment apply to occupations with a labor market tightness that is 7.4% higher ($p = 0.005$) than in the control group. This indicates that the joint treatment also encourages job seekers to change their search behavior, but the opposite behavioral responses to the two treatment elements seem to mask the effects on the effort allocation in columns (1) to (3).

5 Labor Market Effects of Online Job Search Advice

In a next step, we examine the labor market effects of our intervention. Before we present the results of a comprehensive analysis that takes into account potential externalities in Section 5.2, we first compare the average labor market outcomes of treated and non-treated job seekers

[8] Note that the occupation-specific labor market tightness is measured in the first week of the experiment and does not account for potential treatment externalities. We further analyze these effects in Section 5.2 below.

in Section 5.1. Finally, we study heterogeneous treatment effects with respect to the elapsed unemployment duration and the occupation-specific labor market conditions in Section 5.3.

5.1 Preliminary analysis: comparing labor market outcomes of treated and non-treated job seekers

In this section, we present 'naive' estimates of the labor market effects of online job search advice, comparing the employment outcomes of treated and non-treated job seekers in our overall sample. While this strategy resembles the approach followed in many randomized trials, it ignores potential externalities of job search advice. Specifically, we consider three dimensions of individuals' labor market performance: (1) job finding rates to capture the extensive margin of employment, (2) total working hours to account for the extensive and intensive margin of employment and (3) total labor earnings. Figure 2 shows treatment differences relative to the control group, estimated based on Equation (3), for different time periods throughout the first year after the start of the intervention.

As shown in Panel A of Figure 2, the naive estimates show no evidence that the three treatments affect the extensive margin of employment.

With regards to working hours and labor earnings, it can be seen that, in the short run, individuals assigned to the recommendation treatment work more hours and obtain higher earnings compared to the control group. Over the first six months after the start of the experiment, the differences add up to about 6.1 hours worked ($p = 0.068$; see Panel B.1) and DKK1,467 in labor earnings ($p = 0.037$; see Panel C.1), which reflects relative differences of 1.8%, respectively 2.4% compared to the mean of the control group. The initial positive effect of the recommendation treatment diminishes over the course of time, such that we only detect insignificant differences when considering average outcomes accumulated over the first 12 months after the beginning of the intervention.

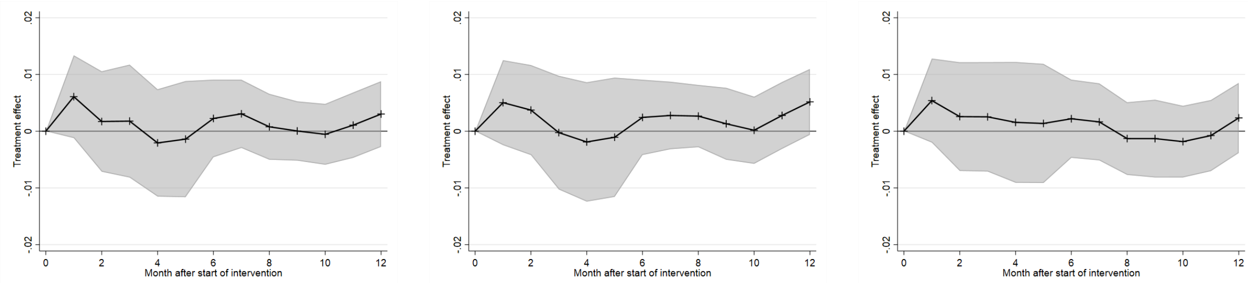
Job seekers assigned to the vacancy treatment also work more hours and obtain higher earnings than the control group, but in contrast to the recommendation treatment, the difference gradually increases over time. After 12 months, job seekers in the vacancy treatment work about 16.8 hours ($p = 0.007$; see Panel B.2) and earn DKK2,684 ($p = 0.028$; see Panel C.2) more than the control group, which reflects relative differences of 2.2%, respectively 1.9%.

When considering the joint treatment, which includes occupational recommendations and vacancy information, we find no significant differences in our naive estimates, relative to the control group.

Figure 2: Comparing labor market outcomes of treated and non-treated over time

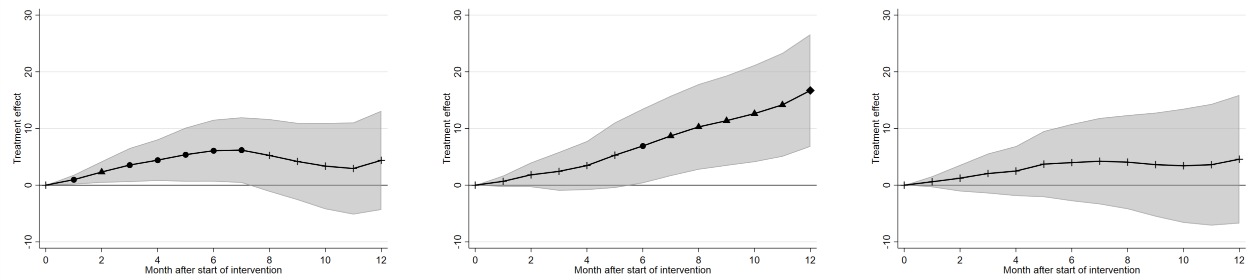
A. Dependent variable: any job finding up until month t

A.1 Recommendation treatment − control group | *A.2 Vacancy treatment − control group* | *A.3 Joint treatment − control group*



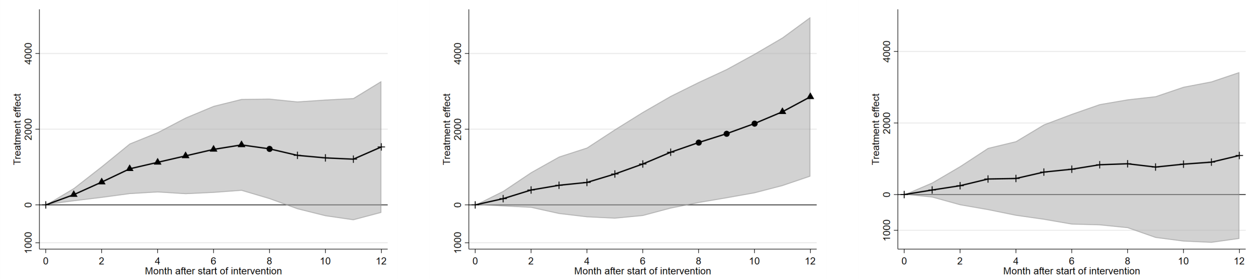
B. Dependent variable: working hours up until month t

B.1 Recommendation treatment − control group | *B.2 Vacancy treatment − control group* | *B.3 Joint treatment − control group*



C. Dependent variable: labor earnings in DKK up until month t

C.1 Recommendation treatment − control group | *C.2 Vacancy treatment − control group* | *C.3 Joint treatment − control group*



Note: The figure shows treatment differences (including 90% confidence intervals) between individuals assigned to each of the three treatment groups (recommendation treatment, vacancy treatment and joint treatment) and the control group. Outcomes are accumulated over the first t months after the start of the intervention (see x-axis). ●/▲/◆ indicates statistical significance at the 10%/5%/1%-level.

5.2 The Direct and Indirect Effects of Online Job Search Advice

The estimates presented in the previous section do not take into account potential externalities that may arise when individuals alter their search strategy in response to job search advice, and thereby change the degree of competition in different occupations. In the presence of such spillovers, the comparison of mean outcomes across treatment groups does not identify the direct effect of job search advice. It rather gives us the sum of the direct effect without treated peers and the difference in weighted averages of spillover effects among treated and non-treated individuals (see, e.g., Vazquez-Bare, 2022).

5.2.1 Econometric specification

To examine the relevance of such externalities we now take advantage of the exogenously induced variation in treatment intensities across municipalities (as shown in Figure 1). In the absence of treatment spillovers, the labor market outcomes of both treated and non-treated individuals should be independent of the local treatment intensity, while spillover effects could have different implications. As discussed in Section 3.3, there could be positive or negative externalities on non-treated job seekers when treated individuals reallocate their effort across occupations. On the one hand, there might be more competition in occupations that become more popular due to our intervention. This could negatively affect the job finding chances of non-treated individuals searching for jobs in these occupations initially. In that case, we expect the labor market outcomes of the control group to decrease with higher treatment intensities. On the other hand, job seekers assigned to the control group could also benefit from higher treatment intensities because treated individuals may apply to different occupations than non-treated individuals, which reduces competition in occupations considered by the control group. Finally, if treated job seekers compete among themselves for jobs, we expect the labor market outcomes of individuals assigned to the treatment groups to decrease with higher treatment intensities.

In the spirit of Crépon *et al.* (2013), we estimate interaction models of the following form:

$$Y_{ij} = \alpha D_i + \gamma TI_j + \delta(D_i \times TI_j) + \beta X_i + \varepsilon_{ij}, \tag{4}$$

where Y_i denotes the outcome variable of interest for individual i, D_i indicates the individual treatment status (recommendation treatment, vacancy treatment, joint treatment or control group) and TI_j characterizes the local treatment intensity, which refers to the share of treated individuals in the job seeker's own municipality j and all neighboring municipalities and varies at the municipality-level. Again, X_i captures a vector of individual-level control variables.

In this setting, the coefficient α approximates the direct treatment effect when the share of other treated individuals is low, while γ identifies possible spillovers on individuals who are assigned to the control group. A positive (negative) coefficient would imply that a larger share of treated individuals has a positive (negative) impact on the labor market outcomes of non-treated job seekers. Finally, the interaction effects of the treatment assignment D_i and the local treatment intensity TI_j, given by δ, inform us about differential spillovers on treated and non-treated individuals. This means that the overall spillover effects on the treatment groups are given by $\gamma + \delta$.

To test the sensitivity of the empirical model with respect to the functional form, we estimate two different specifications. First, we consider the continuous treatment intensity as depicted in

Figure 1. Second, we define indicator variables (based on the continuous measure) identifying regions with low ($TI \leq 0.5$), medium ($0.5 < TI \leq 0.75$) and high ($TI > 0.75$) treatment intensities to test for the presence of non-linear spillover effects. Again, in all specifications, standard errors are clustered at the municipality level.

5.2.2 Balancing and placebo tests

The identification of spillover effects hinges on the assumption that treatment intensities are as good as randomly assigned since the empirical model specified by equation (4) compares non-treated, as well as treated individuals across different regions. We examine the plausibility of this assumption in several ways. First, we compare the characteristics of job seekers who are exposed to low, medium and high treatment intensities. Differences between individuals in the different regions are small and mostly insignificant, as depicted in Table A.1 in the appendix. Moreover, we test to what extent individual characteristics can predict the continuous treatment intensity measure. As shown in Table A.2, regional differences with respect to individual characteristics have little explanatory power (see $p-$values at bottom of Table A.2). Importantly, this is not only the case within the full sample, but also when considering the four treatment groups separately (see columns 2–5 of Table A.2). This suggests that the share of treated individuals is also balanced conditioned on actual treatment assignment, supporting the notion that we identify causal effects of the treatment intensity among different treatment groups.

Finally, we also consider a placebo sample consisting of the stock of UI benefit recipients in March 2018, one year before the start of the experiment. Based on this sample, we test whether the treatment intensity is correlated with labor market outcomes of individuals who were not exposed to the experiment. As shown in Table 5, the treatment intensity is not significantly related to the labor market outcomes of the placebo sample. This further supports the assumption that regions who differ with respect to the assigned treatment intensity are similar in terms of other aspects that are relevant for job seekers' labor market outcomes.

5.2.3 Direct and indirect treatment effects

Table 6 shows the results of the regression characterized by Equation (4) for the three main outcome variables measured within 12 months after the start of the intervention: (1) the job finding probability, (2) total working hours and (3) total labor earnings. It turns out that the labor market effects of online job search advice strongly depend on the fraction of treated individuals within a region.

When considering the continuous measure of treatment intensity (see specification 1 in columns 1–3), we find that the α-coefficients, which approximate the direct effects of job search

Table 5: Effect of local treatment intensity on labor market outcomes of placebo sample

	Specification 1 (continuous)			**Specification 2** (categorical)		
	Outcomes measured within 12 months after start of intervention			Outcomes measured within 12 months after start of intervention		
Dependent variable	Any job finding	Working hours	Labor earnings[(a)]	Any job finding	Working hours	Labor earnings[(a)]
	(1)	(2)	(3)	(4)	(5)	(6)
Local treatment intensity (cont.)	-0.015	-42.3	-6,709			
	(0.021)	(38.5)	(7,304)			
Local treatment intensity (ref. low intensity)						
Medium intensity				-0.014	-27.4	-3,560
				(0.011)	(21.6)	(4,005)
High intensity				-0.009	-23.9	-4,617
				(0.013)	(22.4)	(3,962)
P-value joint sign. treatment intensity				0.472	0.430	0.505
No. of observations	98,452	98,452	98,452	98,454	98,454	98,454
Mean value dep. variable	0.799	774	146,960	0.799	146,960	774

Note: The table reports the results of placebo test, i.e. the effect of the local treatment intensity of the experiment on the labor market outcomes of a historical stock of UI benefit recipients from March 2018 (one year before the start of the intervention). Outcome variables refer to cumulated measures over the subsequent 12 months. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level. The local treatment intensity refers to the share of treated individuals (all three treatment groups) within the job seeker's municipality and all bordering municipalities.
[(a)] Measured in DKK.

advice when the share of other treated individuals is low, are positive and statistically significant for all three treatments. For instance, our estimates imply that job seekers assigned to the recommendation treatment have a 4.1 percentage points higher chance to find employment within the first 12 months (+5.2%; $p = 0.040$), work in total 82.3 hours more (+10.6%; $p < 0.001$), and earn DKK18,412 more than the control group (+12.6%; $p < 0.001$), when the number of other treated individuals approaches zero. The effects of the vacancy information treatment (+13.8% on working hours, respectively +14.4% on labor earnings) are slightly larger than for the recommendation treatment. Notably, we also find that the joint treatment has a positive impact on job seekers' labor market outcomes, but the effects on working hours and earnings tend to be somewhat (albeit insignificantly) smaller than for the recommendation and the vacancy treatments. This suggests that vacancy information and occupational recommendations do not 'add up' when being combined.

At the same time, we find that the labor market outcomes of treated and, to some extent, also those of non-treated job seekers depend on the share of treated individuals within a local labor market. When considering spillovers on the control groups (i.e., the γ-coefficient), we find no evidence that non-treated job seekers are negatively affected by a larger share of treated individuals. If anything, job seekers in the control group, on average, tend to benefit from

Table 6: Direct and indirect treatment effects on labor market outcomes

	Specification 1 (continuous)			**Specification 2** (categorical)		
	Outcomes measured within 12 months after start of intervention			Outcomes measured within 12 months after start of intervention		
Dependent variable	Any job finding	Working hours	Labor earnings[(a)]	Any job finding	Working hours	Labor earnings[(a)]
	(1)	(2)	(3)	(4)	(5)	(6)
Recommendation treatment	0.041**	82.3***	18,412***	0.034**	75.6***	12,746***
	(0.020)	(19.3)	(4,290)	(0.016)	(18.4)	(3,947)
Vacancy treatment	0.048**	107.4***	21,067***	0.044***	73.0***	12,374***
	(0.021)	(28.5)	(6,660)	(0.009)	(15.9)	(3,974)
Joint treatment	0.042**	54.2	12,610*	0.027*	51.6**	11,415**
	(0.015)	(37.9)	(6,581)	(0.014)	(23.3)	(4,490)
Local treatment intensity (cont.)[(b)]	0.023*	16.9	7,915*			
	(0.013)	(26.2)	(4,518)			
× Recommendation treatment	-0.057**	-117.4***	-26,198***			
	(0.027)	(33.1)	(6,883)			
× Vacancy treatment	-0.064**	-135.0***	-27,895**			
	(0.030)	(44.9)	(9,987)			
× Joint treatment	-0.060**	-75.4	-18,323*			
	(0.022)	(58.5)	(9,817)			
Local treatment intensity (ref. low intensity)[(c)]						
Medium intensity				0.009	6.6	3,293*
				(0.007)	(11.2)	(1,748)
× Recommendation treatment				-0.029*	-73.0***	-11,533**
				(0.017)	(23.2)	(4,547)
× Vacancy treatment				-0.039***	-53.1**	-9,389**
				(0.010)	(20.7)	(4,368)
× Joint treatment				-0.025	-47.9*	-11,352**
				(0.015)	(26.7)	(4,982)
High intensity				0.013	15.2	2,993
				(0.009)	(14.3)	(2,616)
× Recommendation treatment				-0.042***	-88.3***	-14,760***
				(0.014)	(13.7)	(2,934)
× Vacancy treatment				-0.046***	-78.8***	-13,107***
				(0.012)	(17.4)	(4,572)
× Joint treatment				-0.030**	-61.4**	-12,282**
				(0.014)	(27.4)	(5,597)
No. of observations	92,098	92,098	92,098	92,098	92,098	92,098
Mean value dep. variable	0.791	779	146,214	0.791	779	146,214
P-value joint sign. treatment intensity						
Control group				0.254	0.491	0.108
Recommendation treatment				0.016	<0.001	<0.001
Vacancy treatment				0.001	<0.001	0.028
Joint treatment				0.132	0.104	0.083

Note: The table reports the results of an interaction model of treatment indicators and local treatment intensities as described by Equation 4 estimated for the actual experimental population. Outcome variables are measured within the first 12 months after the start of the intervention. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level. The local treatment intensity refers to the share of treated individuals (all three treatment groups) within the job seeker's municipality and all bordering municipalities.

[(a)] Measured in DKK.

[(b)] Continuous treatment intensity as depicted in Figure 1.

[(c)] Categorical variable with indicators for low ($TI_j \leq 0.5$), medium ($0.5 < TI_j \leq 0.75$) and high ($TI_j > 0.75$) treatment intensities.

higher treatment intensities. For instance, the estimates in column (3) suggest that raising the treatment intensity by ten percentage points increases the total labor earnings of non-treated job seekers by DKK792 (+0.5%; $p = 0.079$) within one year. A potential rationale for this finding is that non-treated individuals may face less competition when more and more treated job seekers alter their job search strategy in response to the intervention.[9]

The positive spillover effects on the control group are, however, relatively small compared to the negative spillovers on other treated job seekers. It turns out that higher treatment intensities significantly reduce job finding rates, working hours, and labor earnings of job seekers who are assigned to each of the three treatment groups. For instance, increasing the share of treated job seekers by ten percentage points reduces the overall effect of the recommendation treatment on earnings by DKK1,828 [$= 0.1 \times (7,915 - 26,198)$], which reflects an earnings reduction of about 1.3% relative to the sample mean. Similarly, an increase in the treatment intensity by ten percentage points reduces the positive treatment effects of occupational recommendations on working hours by 10.0 hours [$= 0.1 \times (16.9 - 117.4)$]. The corresponding estimates of the negative indirect effects for the vacancy treatment and the joint treatment are very similar in magnitude.

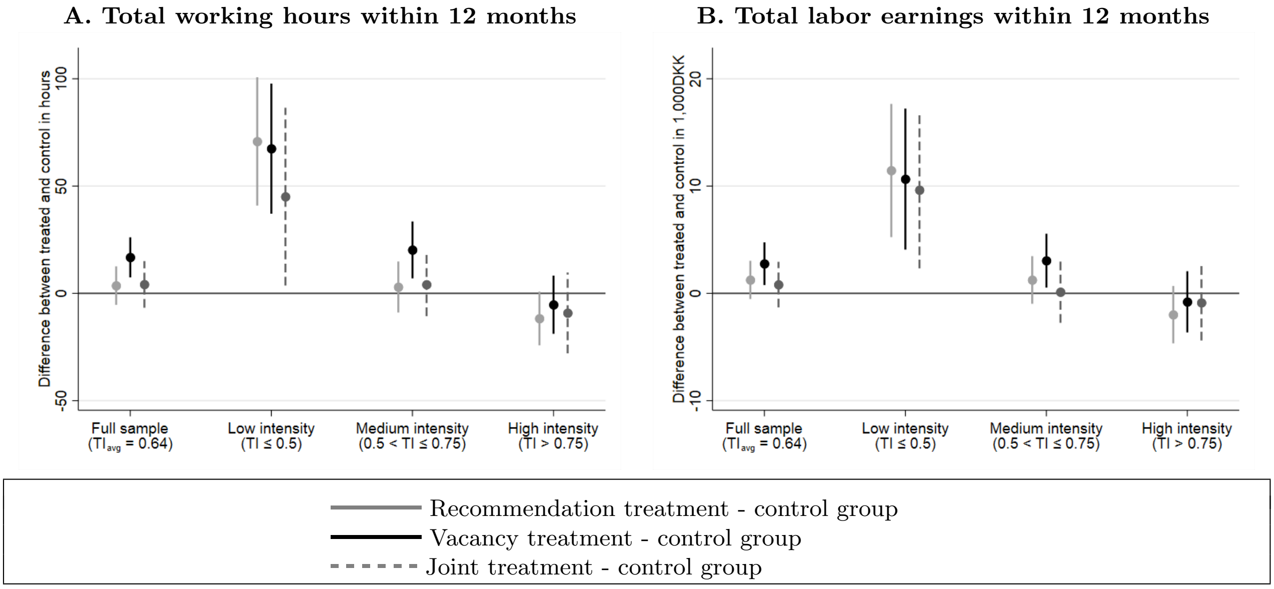
When turning to the categorical measure of treatment intensity (see specification 2 in columns 4-6 of Table 6), we find very similar effects as for the continuous measure. This suggests that there are no indications for strong non-linearities in the indirect effects of our treatments. For example, in regions where less than 50% of the job seekers are exposed to treatment, overall working hours increase by roughly 9.5% for, both, job seekers assigned to the occupational recommendation and vacancy information treatment, whereas labor earnings increase by 8.5-8.7%. The corresponding effect sizes in the joint treatment are 6.6% and 7.8%, respectively. In regions with an intermediate treatment intensity of 50-75%, these effects are substantially smaller, and they are completely washed away when approaching a full roll-out of the treatments (i.e., in regions with a high treatment intensity >75%).

To further illustrate this point, Figure 3 shows differences in labor market outcomes between each of the three treatment groups and the control group separately for regions with a low, intermediate, and high treatment intensity. In low-intensity regions, all three treatment groups work significantly more hours and obtain significantly higher labor earnings than the control group. In regions with intermediate treatment intensities between 50% and 75%, the effect of

[9]It should be noted that the placebo tests presented in Table 5 do not show any statistically significant relationship between local treatment intensities and labor market outcomes of job seekers who were not exposed to the intervention. If anything, unemployed workers in the placebo sample who live in regions with higher treatment intensities tend to accumulate (insignificantly) fewer working hours and lower earnings. Against this backdrop, one could speculate that our estimates of the indirect effects on the control group observed in the experimental population represent a lower bound of the positive spillover effects on non-treated individuals.

the recommendation and the joint treatments turn out to be close to zero and statistically insignificant. Only individuals assigned to vacancy treatment work more hours (+2.6%; $p = 0.012$) and obtain higher earnings (+2.1%; $p = 0.046$) than the control group, but the effects are about 70% smaller than in low-intensity regions. The results from regions with treatment intensities above 75% indicate that none of the treatments has a positive effect on job seekers' employment and earnings prospects.

Figure 3: Conditional differences in outcome variables by local treatment intensity



Note: Depicted are differences in outcome variables between treated (separated for the recommendation, vacancy and joint treatments) and the control group including 90% confidence intervals. Outcome variables are accumulated over the first 12 months after the start of the intervention.

5.2.4 Crowding out of job seekers

The results in the previous section document that exposing a larger share of individuals to online job search advice impairs the labor market performance of treated job seekers. A plausible explanation for this pattern is that treated job seekers, who apply to different occupations in response to the intervention, are more likely to compete among each other in the targeted occupations. At the same time, we also found suggestive evidence that non-treated individuals may benefit from higher treatment intensities, which indicates that they may benefit from the reduced competition because many treated job seekers change their search strategy.

A straightforward way to measure these potential crowding out effects is to consider the number of applications per vacancy. While the data on registered applications from the online portal do not allow us to precisely measure the number of applications for each vacancy, we can construct the ratio of registered job applications and the number of available vacancies at the occupational level. Having obtained such a measure for each occupation, we construct the average number of applications per vacancy for the set of occupations each job seeker applied to within different time intervals after the start of the intervention.[10] Overall, we can measure the occupation-specific competition in job seekers' targeted occupations for about 75% of the experimental population.[11] Using this measure as dependent variable, we re-estimate the regressions characterized by equation (4) to shed light on the changes in occupation-specific competition faced by treated and non-treated job seekers under different treatment intensities.

Column (1) of Table 7 shows the corresponding estimates based on the continuous measure of treatment intensity when considering all applications registered within the first four weeks after the start of the intervention. The findings support the notion that the externalities from online job search advice are indeed provoked by changes in the degree of competition between job seekers across occupations. When treatment intensities are low, treated job seekers in all three treatment arms tend to apply to occupations where they face less competition than non-treated individuals. For instance, job seekers assigned to the recommendation treatment apply to occupations in which the log number of applications per vacancy is about 0.7 lower ($p = 0.032$) than job seekers in the control group. This finding is in line with the changes in job search strategies reported in Section 4—in particular, with the observation that treated job seekers tend to target occupations with an *ex-ante* higher labor market tightness, as documented in Table 4. The finding that, in response to treatment, treated job seekers in low-intensity regions apply to occupations with less competition among applicants is also consistent with the positive direct treatment effects on labor market outcomes reported in Section 5.2.3.

At the same time, we also observe a negative coefficient of the local treatment intensity, which indicates that the control group faces less competition when the share of treated job seekers increases. This pattern is in line with the notion that treated job seekers tend to apply to different occupations than non-treated individuals. The finding is also consistent with the (weak) positive relationship between treatment intensity and labor market outcomes of the control group (see Table 6). The results from Table 7, however, also document that the effects on applicant competition in the occupations targeted by treated job seekers reverse, once the treatment intensity increases. Specifically, we find that treated individuals in regions with higher treatment intensities tend to apply to occupations with more competition, i.e., a higher number of applications per vacancy. This suggests that the negative treatment spillovers on treated individuals are indeed provoked by crowding out among treated job seekers, when more and

[10]Note that the occupational-specific labor market tightness analyzed in Section 4 measures the competition in a certain occupation in the pre-intervention period, whereas we now focus on the competition after treated individuals have been exposed to job search advice.

[11]The number of applications per vacancy is missing (1) for about 9% of the sample who do not register any applications within the first four weeks after the start of the experiment and (2) for about 16% of the sample we cannot match the registered occupations to the occupations obtained in the vacancy database.

Table 7: Crowding out among occupations: number of applications per vacancy

	Specification 1 (continuous)		**Specification 2** (categorical)	
Dependent variable	Log # applications per vacancy in occupations applied to$^{(a)}$		Log # applications per vacancy in occupations applied to$^{(a)}$	
	within four weeks	within 12 months	within four weeks	within 12 months
	(1)	(2)	(3)	(4)
Recommendation treatment	-0.704** (0.329)	-0.354 (0.232)	-0.408* (0.228)	-0.053 (0.138)
Vacancy treatment	-0.661* (0.332)	-0.402 (0.246)	-0.388 (0.229)	-0.124 (0.148)
Joint treatment	-0.791** (0.331)	-0.445* (0.227)	-0.468* (0.239)	-0.129 (0.139)
Local treatment intensity (cont.)$^{(b)}$	-0.922** (0.400)	-0.674*** (0.212)		
× Recommendation treatment	1.106** (0.501)	0.593 (0.351)		
× Vacancy treatment	0.998* (0.509)	0.636 (0.375)		
× Joint treatment	1.221** (0.510)	0.721** (0.348)		
Local treatment intensity (ref. low intensity)$^{(c)}$				
Medium intensity			-0.301 (0.206)	-0.215 (0.129)
× Recommendation treatment			0.428* (0.230)	0.0669 (0.138)
× Vacancy treatment			0.381 (0.231)	0.124 (0.149)
× Joint treatment			0.469* (0.240)	0.134 (0.141)
High intensity			-0.411* (0.217)	-0.234 (0.163)
× Recommendation treatment			0.534** (0.249)	0.120 (0.173)
× Vacancy treatment			0.467* (0.248)	0.170 (0.183)
× Joint treatment			0.614** (0.259)	0.214 (0.174)
No. of observations	68,762	68,762	68,762	68,762
Mean value dep. variable	3.129	4.586	3.129	4.586
P-value joint significance treatment intensity				
Control group			0.184	0.250
Recommendation treatment			0.120	0.786
Vacancy treatment			0.191	0.647
Joint treatment			0.073	0.478

Note: The table reports the results of an interaction model of treatment indicators and local treatment intensities as described by Equation 4 estimated for the actual experimental population. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level. Local treatment intensity refers to the share of treated individuals (all three treatment groups) within the job seeker's municipality and all bordering municipalities.

$^{(a)}$The dependent variable refers to average number of applications per vacancy across the occupations each job seeker applied to within one or 12 months after the start of the intervention.

$^{(b)}$Continuous treatment intensity as depicted in Figure 1.

$^{(c)}$Categorical variable with indicators for low ($TI_j \leq 0.5$), medium ($0.5 < TI_j \leq 0.75$) and high ($TI_j > 0.75$) treatment intensities.

more individuals alter their job search strategy in response to the intervention and eventually target similar occupations.

When considering the effects on applications within the first 12 months after the start of the intervention (see column 2 of Table 7), the overall pattern looks similar, while the coefficients become smaller and partly insignificant. A potential explanation for this finding is that job seekers react to the increased competition by (re-)adjusting their application behavior over time. Finally, the specifications that rely on the categorical measure of treatment intensity, depicted in Columns (3) and (4) of Table 7, show a similar pattern as for the continuous measure of intensity.

5.3 Who benefits from online job search advice?

Given that all three treatments improve labor market outcomes when the share of treated individuals is low, but become less effective for higher treatment intensities, it seems socially optimal to limit the provision of personalized online job search advice to a part of the unemployed population. Against this backdrop, it is crucial to understand which groups of job seekers benefit most strongly from online job search advice in general, and from particular information dashes. In a final step of our analysis, we therefore study heterogeneous treatment effects of our intervention. We focus on two dimensions: (1) the elapsed unemployment duration at the start of the experiment and (2) the labor market tightness among occupations stored in the job seeker's search profile. Both dimensions are expected to be particularly important for job seekers' response to job search advice (see also the theoretical discussion by Kircher, 2022). Moreover, reintegrating long-term unemployed job seekers into the labor market is also prime target for policy-makers.

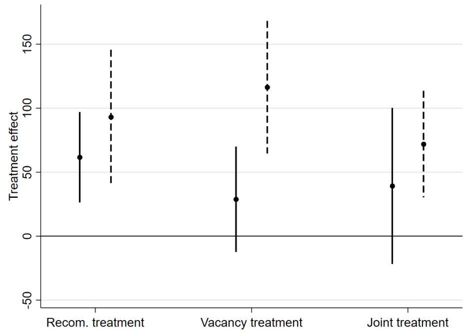
For our empirical analysis, we divide the experimental sample at the median of the two variables and present the treatment effects for the different subgroups in low-intensity regions. We focus our discussion on the effects in low-intensity regions to abstract from spillover effects as much as possible, mimicking a situation where only few job seekers from selected subgroups receive a given form of job search advice. The results from the fully-interacted models are presented in Table A.3 (for the elapsed unemployment duration) and Table A.4 in the appendix (for labor market tightness), respectively.

Elapsed unemployment duration: Previous evidence indicates that labor market policy that aims to support the unemployed during their search process is often more effective for job seekers who are already unemployed for an extended period of time (see, e.g., Altmann *et al.*, 2018; Biewen *et al.*, 2014; Card *et al.*, 2017). As highlighted by Belot *et al.* (2019),

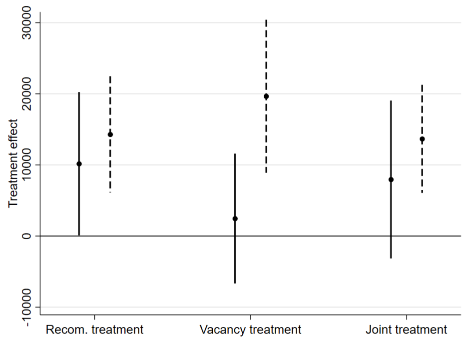
Figure 4: Subgroup analysis: heterogeneous treatment effects in low-intensity regions

A. Subgroup analysis by elapsed unemployment duration

A.1 Working hours within 12 months



A.2 Labor earnings within 12 months

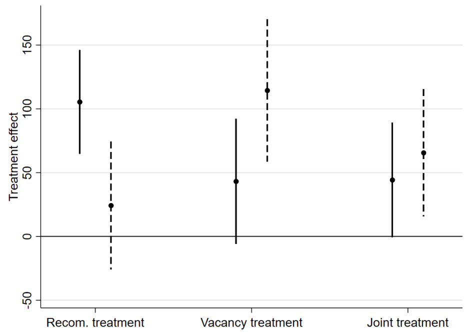


$P-$value (short v. long UE duration)	A.1	A.2
Recommendation treatment:	0.459	0.645
Vacancy treatment:	0.037	0.042
Joint treatment:	0.448	0.480

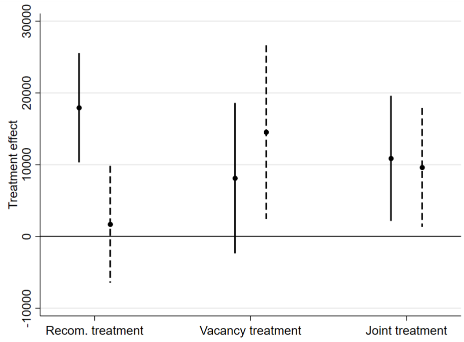
Short UE duration (below median)   Long UE duration (above median)

B. Subgroup analysis by labor market tightness

B.1 Working hours within 12 months



B.2 Labor earnings within 12 months



$P-$value (low v. high tightness)	B.1	B.2
Recommendation treatment:	0.055	0.009
Vacancy treatment:	0.138	0.514
Joint treatment:	0.559	0.839

Low tightness (below median)   High tightness (above median)

Note: Depicted are differences in outcome variables between treated (separated for the recommendation, vacancy and joint treatments) and the control group including 90% confidence intervals in low-intensity region (treatment intensity below 0.5). Outcome variables are accumulated over the first 12 months after the start of the intervention.

job seekers who already search for an extended period without being successful might be more responsive to the information they receive. To examine whether job seekers with a longer elapsed unemployment duration also benefit from the forms of online job search advice studied in our setting, we estimate separate effects on working hours and earnings for job seekers with an elapsed unemployment duration (measured at the start of the intervention) above and below the sample median (=109 days). As shown in Panel A of Figure 4, all three treatments tend to have somewhat larger positive effects on long-term unemployed job seekers, compared to short-term unemployed individuals. The differences in direct treatment effects are most pronounced for the vacancy information treatment. These findings indicate that long-term unemployed job seekers benefit from online job search advice in a similar or even greater extent than short-term unemployed individuals. The targeted provision of online job search advice (exclusively) for long-term unemployed individuals could, thus, be a potentially promising policy to help these workers (while, at the same time, limiting the negative indirect effects of a larger-scale roll-out).

Labor market tightness: As a second dimension of heterogeneity, we consider the labor market tightness in the core occupations stored by a job seeker in her personal job search profile—an indicator of how difficult it is for a given job seeker to find a job in absence of the intervention. Since the expected returns to occupational mobility might be larger for job seekers with relatively poor employment prospects (see e.g. Moscarini and Thomsson, 2007; Moscarini and Vella, 2008), we expect that occupational recommendations are particularly effective for job seekers who would otherwise focus their search activities on occupations with a low tightness (i.e., where we observe few vacancies relative to the number of job seekers). Conversely, we found that the provision of vacancy information is, on average, associated with a stronger focus of job seekers on the core occupations stored in their personal job search profile (see Table 4). Hence, the vacancy information treatment should be particularly effective when a job seeker's personal job search profile provides relatively good job employment prospects, i.e., when the labor market tightness in the job seeker's core occupations is high. The results presented in Panel B of Figure 4 support these ideas. The positive labor market effects of the recommendation treatment are, to a great extent, driven by job seekers with a personal job search profile that is characterized by low labor market tightness. The effect on working hours is about four times larger ($p = 0.055$) in comparison to job seekers who face an above-median labor market tightness in their core occupations. The effect heterogeneity for earnings is even more pronounced ($p = 0.009$). For the vacancy treatment, the pattern looks quite different. While the effects for job seekers with a low vs. high tightness job search profile do not differ significantly from each other, the positive effects are more pronounced among those who face relatively good job prospects in the set of occupations stored in their personal job search profile. For the joint treatment, we observe no heterogeneity in treatment effects for job seekers with a personal job search profile characterized by low vs. high labor market tightness.

Altogether, the observed heterogeneity of the treatment effects in regions with a low treatment intensity is in line with the most likely causal pathways through which the different forms of advice considered in our study are expected to operate. Against this backdrop, one could speculate that a more tailored provision of job search advice, which focuses solely on those groups of job seekers who benefit most strongly from a particular form of advice, may improve welfare by reducing negative spillovers. At the same time, it is important to better understand which job seekers actually compete with each other to determine the optimal degree of personalization, while accounting for the indirect effects of online job search advice on other job seekers.

6 Conclusion

The provision of job search advice is one of the key policies to bring unemployed workers back to employment. The use of digital tools bears great promises in the context of job search advice—thanks to the low cost of online information provision and the possibility to provide tailored advice to different worker groups. In this paper, we provided evidence on the direct and indirect effects of online job search advice, based on a large-scale randomized controlled trial on the official online platform of the Danish employment agency. Our findings demonstrate that two basic forms of tailored advice—the provision of vacancy information and occupational recommendations—can have positive effects on job seekers' employment and earnings prospects. While it has been shown that both occupational referrals (Belot *et al.*, 2019) and vacancy information (Skandalis, 2018; Gee, 2019) can encourage job seekers to adjust their search behavior, we provide first evidence that both types of job search advice can have substantial positive effects on subsequent employment and earnings. This suggests that information frictions might be a distorting factor in the job search process and that online tools providing basic information can mitigate some of these friction.

Although both types of job search advice have employment and earnings effects in the same order of magnitude, we document that they are associated with very different adjustments of job seekers' behavior. While occupational recommendations encourage job seekers to apply to alternative occupations, job seekers receiving vacancy information focus their search activities on a more narrow set of occupations. Moreover, providing both types of advice at the same time does not lead to larger employment or earnings effects than the two separate forms of advice alone. This indicates that different forms of advice can potentially offset each others' effects, which should be accounted for by policy makers when determining how to best combine potentially valuable policy tools.

One of the central results of our analysis is the fact that the positive direct effects of online job search advice can be partially or fully offset by negative indirect effects. In particular, when more and more job seekers are exposed to similar forms of advice, this can lead to spillovers between job seekers. While there is suggestive evidence that job seekers assigned to the control group tend to benefit from a larger share of treated individuals, we find large negative spillovers on other treated job seekers. Our results suggest that these negative spillovers are provoked by job seekers who, in response to receiving advice, alter their job search strategy in a way that eventually leads to increased competition among job seekers in the newly targeted occupations.

The presence of strong spillover effects are of high relevance for researchers and policy-makers alike. On the one hand, our results provide a cautionary tale that policy interventions, which have proven successful at a smaller scale, might be difficult to roll out for the population at large (Muralidharan and Niehaus, 2017; Al-Ubaydli *et al.*, 2017, 2019). On the other hand, our results also suggest possible avenues on how to design online advice systems that have direct benefits for some job seekers, while limiting negative externalities for others. In this respect, it appears promising to provide tailored advice to subgroups of workers who benefit most strongly from a particular form of advice. For example, our results show that occupational recommendations primarily improve the labor market outcomes of job seekers who were initially searching in occupations with relatively poor labor market prospects, while vacancy information are more effective among unemployed workers targeting occupations with favorable conditions. With this in mind, our findings open up a rich set of research possibilities for analyzing how 'optimal' personalized advice tools should be designed. Besides exploiting heterogeneities and potential mismatch in different segments of the labor market, a particularly promising avenue in this respect seems to develop online tools that elicit and condition on a richer set of commonly unobserved individual characteristics. These could, for instance, include workers' 'soft' or non-cognitive skills (as measured, e.g., through aptitude tests) or their preferences over non-wage job characteristics.

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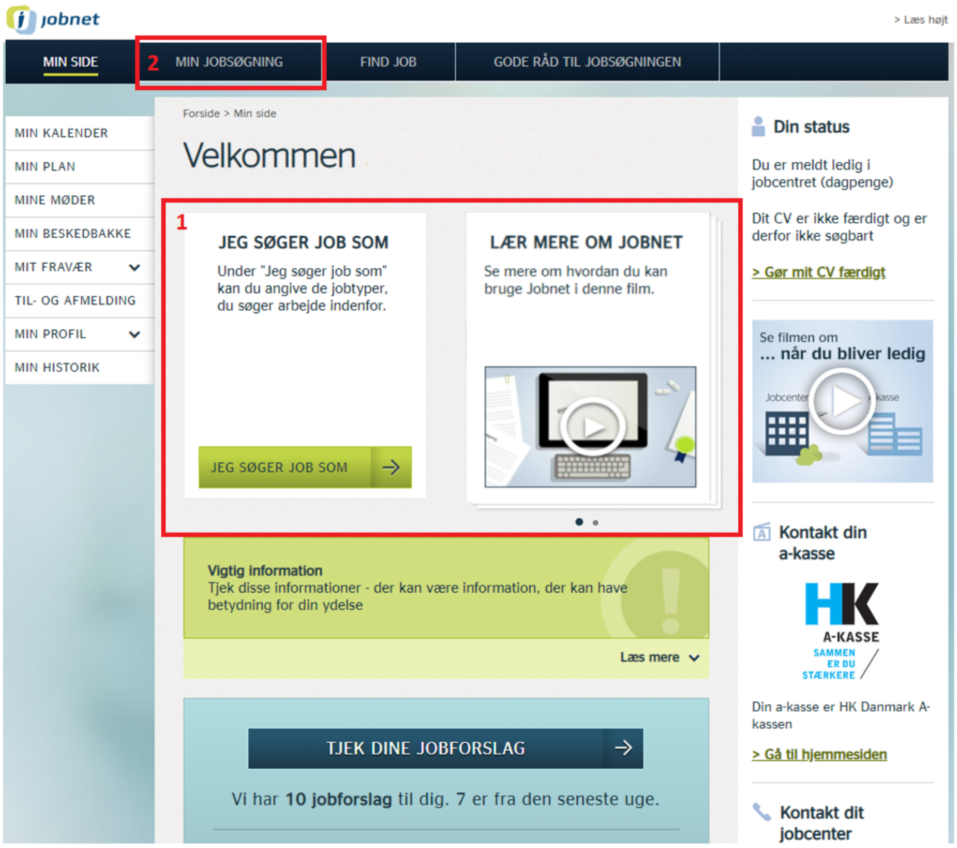
A Appendix

Figure A.1: Job seekers' main personal page on the jobnet.dk plaform



Note: Depicted is a screenshot of the landing page of the online portal of the Danish employment agency *jobnet.dk*. The red box marked by (1) shows the dashboard, while the tab marked by (2) direct job seekers to their personal profile where they can store preferred occupations and register their applications.

Figure A.2: Content of Dashboard

(A) Vacancy recommendation

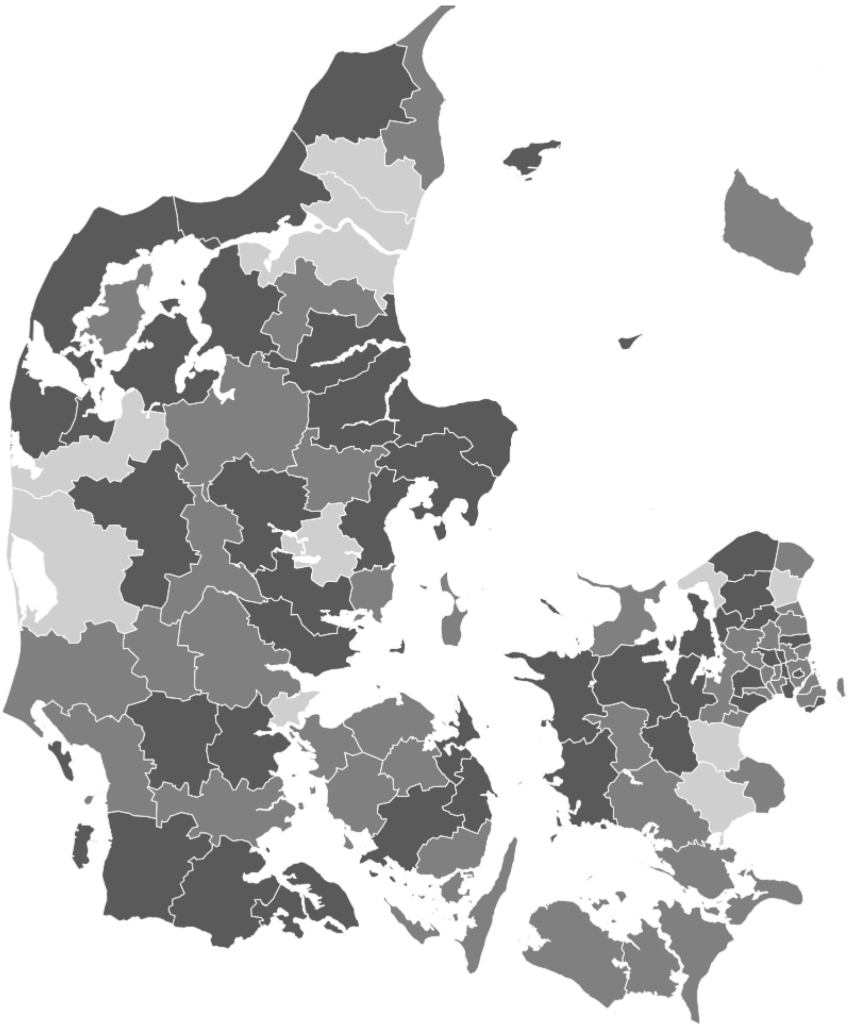
(B) Occupational information

(C) Video

(D) Search profile

A: Within your local area, there are currently 37 vacancies available in occupations in which you are searching for a job.
B: You are searching for a job as "canteen manager". The following occupations could be also relevant for you: chef de cuisine; kitchen staff; chef.
C: Learn more about how you can use Jobnet in this video.
D: Under "I am looking for a job as", you can specify which types of jobs you are searching for.

Figure A.3: Geographical distribution of assignment groups



Note: The figure depicts the geographical distribution of municipalities in different assignment groups (cp. Table 2).
Light-gray: super control (100% non-treated)
Medium-gray: 60% assignment (20% in each treatment group; 40% non-treated)
Dark-gray: 90% assignment (30% in each treatment group; 10% non-treated)

Table A.1: Summary statistics and balancing tests by local treatment intensity

	Placebo sample				**Experimental sample**			
	Mean values by treat. intensity			Balancing stat.	Mean values by treat. intensity			Balancing stat.
	Low	Medium	High	$P-$value	Low	Medium	High	$P-$value
No. of observations	11,658	63,257	23,726		10,746	59,032	22,320	
Educational level								
Lower secondary (or lower)	0.195	0.174	0.181	0.821	0.213	0.184	0.197	0.668
Upper secondary	0.445	0.385	0.420	0.255	0.453	0.402	0.440	0.330
BA or equivalent	0.223	0.244	0.242	0.878	0.239	0.270	0.255	0.713
MA or equivalent	0.068	0.108	0.084	0.360	0.068	0.110	0.084	0.196
Male	0.491	0.473	0.489	0.102	0.484	0.468	0.474	0.469
Age								
18 - 25 years	0.139	0.106	0.133	0.086	0.132	0.103	0.126	0.129
26 - 35 years	0.305	0.333	0.341	0.786	0.315	0.336	0.342	0.850
36 - 45 years	0.180	0.201	0.177	0.049	0.178	0.197	0.177	0.091
46 - 55 years	0.197	0.199	0.186	0.907	0.190	0.195	0.180	0.844
56 - 65 years	0.179	0.161	0.163	0.837	0.185	0.170	0.175	0.881
Married or cohabiting	0.344	0.342	0.336	0.993	0.556	0.549	0.561	0.979
Any children	0.318	0.338	0.336	0.756	0.369	0.369	0.374	0.991
Migration background	0.158	0.247	0.207	0.002	0.163	0.247	0.216	0.000
Elapsed benefit duration (in days)	181.2	187.1	181.5	0.422	171.0	173.0	171.2	0.912
Avg. monthly labor earnings (in DKK)								
in last year	17,716	18,194	16,864	0.575	18,218	18,788	17,765	0.583
in last three years	18,718	19,359	17,975	0.602	19,422	20,082	18,831	0.558
Avg. weekly working hours								
in last year	19.86	19.15	18.72	0.798	19.42	19.05	18.82	0.921
in last three years	22.60	22.35	21.76	0.921	22.51	22.30	21.89	0.941
Previous occupation before unemployment								
Managerial position	0.016	0.017	0.014	0.196	0.019	0.021	0.017	0.346
Professional position	0.182	0.219	0.206	0.639	0.129	0.158	0.147	0.102
Technicians and associated position	0.061	0.077	0.071	0.047	0.054	0.066	0.060	0.086
Clerical support worker	0.089	0.109	0.103	0.028	0.078	0.100	0.086	0.060
Service sales worker	0.211	0.208	0.216	0.673	0.202	0.198	0.207	0.628
Agricultural worker	0.011	0.010	0.013	0.718	0.008	0.006	0.007	0.618
Craft worker	0.084	0.067	0.071	0.298	0.073	0.051	0.058	0.099
Plant machine operator	0.089	0.062	0.068	0.223	0.061	0.046	0.056	0.569
Elementary occupation	0.200	0.181	0.190	0.615	0.155	0.149	0.155	0.841
Labor market tightness	0.101	0.116	0.118	0.251	0.133	0.164	0.157	0.066

Note: Percentage shares unless indicated otherwise. $P-$values are based on F-tests for joint significance of treatment intensity coefficients in separate regressions of each of the characteristics on dummies for the different levels of treatment treatment intensities.
Low - treatment intensity ≤ 0.5; Medium - $0.5 <$ treatment intensity ≤ 0.75; High - treatment intensity > 0.75.

Table A.2: Determinants of local treatment intensity (continuous)

	Full sample (1)	Treatment status: Control group (2)	Recom. treatment (3)	Vacancy treatment (4)	Joint treatment (5)
Dependent variable: local treatment intensity					
Age (ref. 18 - 25 years)					
26 - 35 years	0.0014	0.0062	-0.0012	-0.0018	-0.0011
	(0.0028)	(0.0045)	(0.0027)	(0.0031)	(0.0035)
36 - 45 years	-0.0027	0.0079	-0.0058	-0.0077	-0.0126*
	(0.0049)	(0.0058)	(0.0047)	(0.0054)	(0.0068)
46 - 55 years	-0.0021	0.0084	-0.0068	-0.0062	-0.0112*
	(0.0057)	(0.0077)	(0.0069)	(0.0061)	(0.0062)
56 - 65 years	-0.0030	0.0093	-0.0090	-0.0088	-0.0116
	(0.0068)	(0.0085)	(0.0078)	(0.0074)	(0.0077)
Married	-0.0004	-0.0082*	0.0041	0.0047	0.0023
	(0.0033)	(0.0044)	(0.0036)	(0.0039)	(0.0049)
Male	0.0007	-0.0035	0.0027	0.0028	0.0041
	(0.0023)	(0.0035)	(0.0026)	(0.0027)	(0.0028)
Any children	0.0004	0.0082	-0.0033	-0.0053	-0.0027
	(0.0036)	(0.0064)	(0.0035)	(0.0036)	(0.0032)
Danish	-0.0111*	-0.0150**	-0.0060	-0.0104	-0.0103
	(0.0058)	(0.0073)	(0.0056)	(0.0072)	(0.0065)
Level of education (ref. no secondary or missing)					
Lower secondary	0.0073	0.0127	0.0008	0.0026	0.0073*
	(0.0050)	(0.0091)	(0.0062)	(0.0061)	(0.0042)
Upper secondary	0.0070*	0.0074	0.0008	0.0090*	0.0088*
	(0.0037)	(0.0062)	(0.0049)	(0.0049)	(0.0046)
BA or equivalent	0.0088*	0.0045	0.0075	0.0111*	0.0138**
	(0.0046)	(0.0040)	(0.0054)	(0.0063)	(0.0069)
MA or equivalent	0.0110	0.0052	0.0101	0.0141	0.0168
	(0.0081)	(0.0078)	(0.0098)	(0.0107)	(0.0108)
Elapsed unemployment duration (ref. less than one month)					
1 - 3 months	-0.0010	-0.0056**	0.0054*	0.0004	-0.0002
	(0.0017)	(0.0026)	(0.0028)	(0.0025)	(0.0031)
4 - 6 months	-0.0037**	-0.0079***	0.0010	-0.0003	-0.0044
	(0.0018)	(0.0028)	(0.0034)	(0.0035)	(0.0029)
7 - 12 months	-0.0012	-0.0078*	0.0071**	0.0015	-0.0002
	(0.0023)	(0.0040)	(0.0033)	(0.0026)	(0.0032)
13 - 24 months	-0.0015	-0.0107**	0.0101*	0.0001	0.0012
	(0.0028)	(0.0046)	(0.0051)	(0.0029)	(0.0037)
more than 24 months	0.0013	0.0032	-0.0071	0.0045	0.0032
	(0.0046)	(0.0059)	(0.0098)	(0.0087)	(0.0084)

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Labor earnings in year $t-x$ (in 100,000DKK)					
t - 1	0.0060	0.0017	0.0041	0.0095	0.0106
	(0.0073)	(0.0074)	(0.0104)	(0.0090)	(0.0095)
t - 2	0.0003	0.0061	-0.0045	0.0011	-0.0001
	(0.0030)	(0.0121)	(0.0057)	(0.0030)	(0.0053)
t - 3	0.0003	0.0074	0.0115	-0.0125	-0.0145
	(0.0062)	(0.0081)	(0.0126)	(0.0095)	(0.0135)
Average weekly working hours ($\times 100$) in year $t-x$					
t - 1	-0.0127	-0.0030	-0.0041	-0.0326*	-0.0133
	(0.0124)	(0.0114)	(0.0175)	(0.0166)	(0.0165)
t - 2	0.0040	0.0107	-0.0066	0.0068	-0.0086
	(0.0081)	(0.0170)	(0.0098)	(0.0095)	(0.0105)
t - 3	-0.0189	0.0033	-0.0427**	-0.0253	-0.0195
	(0.0156)	(0.0128)	(0.0188)	(0.0227)	(0.0239)
Previous occupation (ref. none)					
Managerial position	0.0053	0.0083	-0.0074	0.0125*	0.0048
	(0.0049)	(0.0071)	(0.0082)	(0.0071)	(0.0065)
Professional position	0.0071*	0.0095*	-0.0012	0.0076*	0.0106**
	(0.0036)	(0.0049)	(0.0050)	(0.0045)	(0.0052)
Technicians and associated position	0.0108*	0.0149**	0.0041	0.0132*	0.0089
	(0.0055)	(0.0059)	(0.0069)	(0.0072)	(0.0072)
Clerical support worker	0.0086*	0.0121**	0.0036	0.0080	0.0090
	(0.0049)	(0.0059)	(0.0061)	(0.0058)	(0.0064)
Service sales worker	0.0037	0.0035	0.0009	0.0041	0.0063
	(0.0030)	(0.0040)	(0.0033)	(0.0045)	(0.0043)
Agricultural worker	-0.0032	-0.0029	-0.0112	-0.0032	0.0049
	(0.0079)	(0.0129)	(0.0142)	(0.0119)	(0.0130)
Craft worker	0.0003	0.0051	-0.0095	0.0008	0.0002
	(0.0032)	(0.0046)	(0.0057)	(0.0059)	(0.0049)
Plant machine operator	0.0027	0.0114	-0.0093	-0.0013	0.0055
	(0.0090)	(0.0096)	(0.0095)	(0.0118)	(0.0123)
Elementary occupation	0.0035	0.0063**	-0.0049	0.0037	0.0074*
	(0.0022)	(0.0030)	(0.0033)	(0.0039)	(0.0041)
Labor market tightness	0.0108*	0.0238**	0.0021	0.0055	0.0053
	(0.0059)	(0.0111)	(0.0045)	(0.0086)	(0.0054)
Constant	0.4177***	0.4080***	0.6609***	0.6578***	0.6551***
	(0.0850)	(0.0857)	(0.0105)	(0.0108)	(0.0104)
No. of observations	92,098	31,966	19,990	20,225	19,917
Mean value dep. variable	0.644	0.581	0.679	0.678	0.677
P-value joint significance	0.777	0.621	0.634	0.302	0.702

Note: Depicted are coefficients of an ordered probit model. The dependent variable refers to the categorical measure of the local treatment intensity (either low, medium or high). Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level. Local treatment intensity refers to the share of treated individuals (all three treatment groups) within the job seeker's municipality and all bordering municipalities.

Table A.3: Subgroup analysis by elapsed unemployment duration

Dependent variable	Total working hours within 12 months		Total labor earnings within 12 months[a]	
	Short UE duration (below median)	Long UE duration (above median)	Short UE duration (below median)	Long UE duration (above median)
	(1)	(2)	(3)	(4)
Recommendation treatment	61.7***	93.1***	10,167*	14,285***
	(21.5)	(32.0)	(6,121)	(4,971)
Vacancy treatment	28.9	116.4***	2,459	19,653***
	(25.1)	(31.5)	(5,552)	(6,540)
Joint treatment	39.3	72.0***	7,957	13,665***
	(37.1)	(25.3)	(6,748)	(4,615)
Local treatment intensity (ref. low intensity)[b]				
Medium intensity	-3.8	9.3	1,311	4,704
	(14.7)	(19.8)	(2,244)	(3,057)
× Recommendation treatment	-59.5**	-89.0***	-7,782	-14,002***
	(23.8)	(33.2)	(6,446)	(5,197)
× Vacancy treatment	-9.2	-98.5***	1,157	-18,023***
	(26.8)	(33.1)	(5,821)	(6,844)
× Joint treatment	-44.5	-60.8**	-8,712	-12,839**
	(38.2)	(27.8)	(6,984)	(5,104)
High intensity	19.3	0.4	2,986	279
	(18.0)	(20.3)	(2,932)	(3,595)
× Recommendation treatment	-85.1***	-91.8**	-12,913*	-14,181**
	(26.1)	(34.9)	(6,916)	(5,634)
× Vacancy treatment	-48.5*	-107.0***	-3,808	-18,749**
	(29.0)	(34.9)	(6,639)	(7,312)
× Joint treatment	-58.2	-72.9**	-9,458	-13,169**
	(39.8)	(31.0)	(7,394)	(5,775)
No. of observations	45,944	46,154	45,944	46,154
Mean value dep. variable	867.3	697.0	163,731	123,989

Note: The table reports the results of an interaction model of treatment indicators and local treatment intensities as described by Equation 4 estimated for the actual experimental population. Outcome variables are measured within the first 12 months after the start of the intervention. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level. The local treatment intensity refers to the share of treated individuals (all three treatment groups) within the job seeker's municipality and all bordering municipalities.
[a] Measured in DKK.
[b] Categorical variable with indicators for low ($TI_j \leq 0.5$), medium ($0.5 < TI_j \leq 0.75$) and high ($TI_j > 0.75$) treatment intensities.

Table A.4: Subgroup analysis by labor market tightness in core occupations

Dependent variable	Total working hours within 12 months		Total labor earnings within 12 months[(a)]	
	Low labor market tightness (below median)	High labor market tightness (above median)	Low labor market tightness (below median)	High labor market tightness (above median)
	(1)	(2)	(3)	(4)
Recommendation treatment	105.5***	24.3	17,943***	1,690
	(24.8)	(30.5)	(4,629)	(4,950)
Vacancy treatment	43.2	114.5***	8,120	14,538*
	(29.9)	(34.0)	(6,371)	(7,362)
Joint treatment	44.4	65.6**	10,881**	9,628*
	(27.4)	(30.3)	(5,300)	(5,035)
Local treatment intensity (ref. low intensity)[(b)]				
Medium intensity	-0.2	-11.1	3,005	-872
	(16.4)	(14.7)	(2,847)	(2,532)
× Recommendation treatment	-108.8***	-17.4	-17,653***	117
	(26.5)	(31.5)	(5,001)	(5,266)
× Vacancy treatment	-14.7	-105.7***	-3,705	-13,504*
	(31.0)	(35.4)	(6,523)	(7,513)
× Joint treatment	-41.9	-62.6*	-11,529**	-8,966*
	(28.6)	(31.7)	(5,476)	(5,375)
High intensity	20.6	-17.4	3,348	-3,836
	(18.2)	(20.6)	(2,990)	(3,561)
× Recommendation treatment	-125.9***	-29.4	-20,085***	-3,003
	(29.0)	(35.4)	(5,501)	(5,832)
× Vacancy treatment	-56.3*	-113.0***	-9,687	-13,696*
	(32.4)	(38.0)	(6,834)	(7,997)
× Joint treatment	-58.7*	-71.3*	-11,914**	-9,734
	(31.5)	(36.1)	(5,994)	(6,140)
No. of observations	46,049	46,049	46,049	46,049
Mean value control low	743.3	842.6	133,737	159,843

Note: The table reports the results of an interaction model of treatment indicators and local treatment intensities as described by Equation 4 estimated for the actual experimental population. Outcome variables are measured within the first 12 months after the start of the intervention. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level. The local treatment intensity refers to the share of treated individuals (all three treatment groups) within the job seeker's municipality and all bordering municipalities.
[(a)]Measured in DKK.
[(b)]Categorical variable with indicators for low ($TI_j \leq 0.5$), medium ($0.5 < TI_j \leq 0.75$) and high ($TI_j > 0.75$) treatment intensities.