The Direct and Indirect Effects of Online Job Search Advice*

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

September 2023

Abstract

We study how online job search advice affects the job search behavior and labor market outcomes of unemployed workers. In a large-scale field experiment, we provide job seekers with vacancy information and occupational recommendations through 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 and significantly increases job seekers' working hours and labor earnings when the share of treated workers is relatively low. 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 to the same vacancies. The negative indirect effects completely offset the positive direct effects of search advice when approaching a full roll-out.

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

*This study was conducted as a part of the research initiative 'Behavioral Economics and Labor Market Performance'. Financial support by the Danish Ministry of Employment is gratefully acknowledged. We are grateful to Simon Lamech and the team of the Danish Agency for Labor Market and Recruitment for their invaluable support in the implementation of our study.

†University of Hohenheim, University of Copenhagen and IZA Bonn; steffen.altmann@uni-hohenheim.de

‡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 (Altmann *et al.*, 2022; Chetty and Saez, 2013), the returns to occupational flexibility (Belot *et al.*, 2019), or their overall employment prospects (Mueller *et al.*, 2021; Mueller and Spinnewijn, 2022; Spinnewijn, 2015). 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 (see Kircher, 2022, for an overview).

Similar to other economic settings, digital advice bears two distinct promises in the context of job search. First, it enables policymakers 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 evident in settings with non-rival goods (see, e.g., Goldfarb and Tucker, 2019), the competitive nature of labor markets can induce spillover effects on other market participants (see Crépon *et al.*, 2013; Gautier *et al.*, 2018). These indirect effects have to be weighed against the direct effects of advice on the individuals who actually receive assistance.

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∼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 search advice commonly found within online job marketplaces, 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 treatment*, we provide each job seeker with information regarding the quantity of vacant positions in occupations aligning with their personal job search profile. In a second treatment, the *recommendation*

[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).

treatment, job seekers receive referrals to suitable alternative occupations that might be a good fit for them based on their personal job search profile. These occupational recommendations were derived from data on successful recent labor market transitions made by comparable 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 the 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., Altmann *et al.*, 2019; Kudlyak *et al.*, 2013) are therefore less of a concern in our setup. Second, since participants are logged into the platform, we can customize the advice based on the individual characteristics of job seekers. Specifically, in our setting, unemployed individuals are mandated to define a personal job search profile, which includes the specific occupations they are seeking employment in. 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. Lastly, our setup enables 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. In particular, we examine 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, while these effects vary systematically across treatments. Job seekers who receive occupational referrals tend to align with the recommendations, resulting in more frequent applications to the suggested occupations. Conversely, among job seekers exposed to the vacancy treatment, we observe an increased focus on their 'core' occupations that were already stored in the job seekers' personal job search profile prior to 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. This aligns with the observation that the two types of information have countervailing effects on job seekers' application behavior. Finally, for all forms of online job search advice considered, we consistently observe that treated individuals tend to apply to occupations with more favorable overall conditions compared to the control group. These occupations were initially characterized by a lower number of job seekers per vacancy, suggesting that the altered job search strategy has the potential to improve job seekers' reemployment prospects.

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 comprehensive understanding of the direct and indirect effects of online job search advice on both treated and untreated job seekers. By altering the competitive pressure among applicants in various occupations, job search advice may give rise to distinct types of externalities (see, e.g., Kircher, 2022). On the one hand, it can enhance the matching process by guiding job seekers towards high-demand occupations with numerous job vacancies. On the other hand, there exists a potential risk of congestion effects if an excessive number of job seekers are prompted to apply for the same set of vacancies. 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. A first comparison, disregarding the possibility of treatment spillovers, suggests modest labor market effects resulting from the various treatments. However, when accounting for externalities, it becomes evident that these effects vary significantly across local labor markets with differing treatment intensities. To be specific, we find significant positive effects of online job search advice when the proportion of treated individuals in a local labor market is relatively low:[2] in regions situated within the bottom tercile of the treatment intensity distribution, both occupational recommendations and vacancy information increase labor earnings and overall working hours of treated job seekers by 4.0–4.5% 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"

[2] In our main analysis, we determine the local treatment intensity within a specific municipality by taking into account the proportion of treated job seekers across all municipalities, weighted by the municipality-specific commuting flows.

when being combined. While individuals assigned to the joint treatment still exhibit higher employment and earnings levels than those in the control group, point estimates are statistically insignificant and smaller than those for the recommendation and vacancy treatments.

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 falling within the top tercile of the treatment intensity distribution, the working hours and earnings of individuals assigned to any 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; Cheung *et al.*, 2019; Crépon *et al.*, 2013; Gautier *et al.*, 2018).

A further examination of registered job applications suggests that the observed indirect effects are provoked by crowding out among treated job seekers who apply for similar occupations. Our intervention affects the allocation of job applications, with treated job seekers in regions experiencing high treatment intensities tending to apply for occupations where they encounter more competition from other treated individuals. We observe that aggregate labor market outcomes, in our setting, reach their peak at intermediate treatment intensities. However, as the proportion of treated increases further, congestion effects become more pronounced, reducing the matching efficiency.

Our findings contribute to several strands of the literature. Most directly related is a nascent body of research on online job search advice, which was initiated by Belot *et al.* (2019) and further investigated in a number of contemporaneous studies by Belot *et al.* (2023), Belot *et al.* (2022), Behaghel *et al.* (2022), Ben Dhia *et al.* (2022) and Le Barbanchon *et al.* (2023). 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.[3] Our study provides a number of important new insights to this literature. First, by studying occupational recommendations as well as

[3] 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. Subsequent studies suggest that occupational referrals stimulate employment among long-term unemployed (Belot *et al.*, 2022) and among job seekers in structurally poor labor markets (Belot *et al.*, 2023). Furthermore, Behaghel *et al.* (2022) and Le Barbanchon *et al.* (2023) document positive employment effects when guiding job seekers to direct their applications towards establishments that are likely to recruit and specific job postings, respectively, with limited congestion effects. 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.

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.[4] This indicates that information frictions and, more generally, labor supply constraints could hamper job seekers' labor market integration (see also Abebe *et al.*, 2021; Alfonsi *et al.*, 2020; Caria *et al.*, 2022). 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, we provide first evidence that the negative indirect effects of online job search advice can indeed be substantial, potentially completely offsetting the positive direct effects.

In doing so, our results also contribute to a growing literature that documents spillover effects in various economic applications, including labor market policy (Albrecht *et al.*, 2009; Lalive *et al.*, 2015; Lise *et al.*, 2004), 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 Al-Ubaydli *et al.*, 2017, 2019; Muralidharan and Niehaus, 2017, for general overviews). Therefore, it appears important that researchers and policymakers 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 (see also Bied *et al.*, 2023, for a more comprehensive discussion). 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

[4]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).

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 overviews), caseworker counseling (Behaghel *et al.*, 2014; Schiprowski, 2020), and information provision (Altmann *et al.*, 2018, 2022; Benghalem *et al.*, 2021; Crépon *et al.*, 2018) 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 remainder of the paper is organized as follows: The next section presents the design of our experiment. Section 3 outlines the potential direct and indirect effects of online job search advice, viewed through the lens of a search and matching framework. Moving on, Sections 4 and 5 present the empirical results regarding how our intervention influences job seekers' application behavior and labor market outcomes, respectively. Finally, Section 6 concludes.

2 Study Design

To study the labor market effects of online job search advice, we rely on a digital dashboard that is embedded in the official online platform of the Danish public employment service (*jobnet.dk*). This setting enables us to customize and 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 details of our randomized controlled trial.

2.1 The dashboard

The dashboard is integrated into the landing page of jobnet.dk, which job seekers encounter immediately upon logging in to the online platform. This is illustrated in Figure A.1 in the Appendix, where the dashboard is displayed in the upper central section of the screen (indicated by the red box labeled as (1)). Due to the dashboard's prominent placement and the widespread use of the platform—it is mandatory for all UI benefit recipients in Denmark to log in at least once a week—it offers an ideal environment for investigating the impacts of online job search advice. On the one hand, the dashboard enables us to exogenously vary the information provided to job seekers in a natural manner, simply by adjusting which dashes are presented to a particular job seeker. On the other hand, the information delivered via the dashboard can be customized to suit each job seeker's personal situation. More precisely, 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 encompasses a selection of occupations in which the individual expresses an interest in working. Job seekers can choose from approximately 1,020 potential occupations, categorized according to the Danish version of the international occupation classification system ISCO. Using these profiles as a foundation, the dashboard delivers personalized vacancy information and occupational recommendations to job seekers through various information cards, which we will elaborate on in the following sections.

Vacancy information: The first information card informs job seekers about the current total of available vacancies for the specific occupations saved in their personal profile (see Panel A of Figure A.2 in the Appendix). This information relates to job openings posted within a 50 km radius of the individual's residential zip code. It undergoes daily updates and draws from the vacancy database on the jobnet.dk platform, encompassing over 90% of all listed vacancies in Denmark. The vacancy data is accompanied by a link to the online platform's subpage, allowing job seekers to review and, if necessary, modify their personal job search profile.

Occupational recommendations: The second information card, displayed in Panel B of Figure A.2, offers job seekers recommendations for related alternative occupations based on the ones they have specified in their personal job search profile. Every time a job seeker logs into 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. Following Belot *et al.* (2019), we generated these 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 during the period 2013-2016. While many workers managed to secure 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 frequent transitions (i.e., the most popular alternative occupations for each "source" occupation).[5] he information card displays a maximum of three out of these five potential alternative occupations, provided that these alternatives are not already stored in the job seeker's personal job search profile. Job seekers can conveniently access a list of all currently available vacancies related to the recommended alternative occupations by clicking on the suggested occupation. Similarly, just as with the vacancy information dashboard, job seekers can click on a link to access and potentially modify their personal job search profile.

Generic information: In addition to the two cards containing personalized, occupation-specific information, the dashboard also includes two generic information cards that do not offer personalized content. One card (see Panel C of Figure A.2) provides a link to a video offering general information about the features and functionalities of the online platform. The other card (see Panel D of Figure A.2) offers a link to the subpage of the online platform where job seekers can make adjustments to their personal job search profile. As explained in more detail in Section 2.2, these two generic information cards are presented to individuals assigned to the control group in our experiment. Furthermore, the generic cards also serve as placeholders to "fill up" the dashboard for job seekers in certain other treatment groups in our experiment (see additional 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. Each job seeker's dashboard features two out of the four information cards, and the individual's treatment status determines which cards are displayed (see Table 1 for an overview).

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)

Note: The table summarizes the assignment of information cards displayed on job seekers' dashboard across treatment groups. The information cards are visualized in Figure A.2 in the Appendix.

[5] 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.

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. Since these cards only provide basic information that would be straightforward to obtain without the dashboard, we anticipate that their impact on job seekers' behavior will be minimal. In addition, we randomly assigned job seekers to three treatment groups, enabling us to identify the causal effects of occupational recommendations, vacancy information, and their combined effect. Job seekers assigned to the *recommendation treatment* encounter the card containing occupational recommendations (B) along with the generic video card (C). Those in the *vacancy treatment* receive information about the number of available vacancies in the occupations stored in their personal job search profile (A) in addition to the generic video card (C). Lastly, individuals assigned to the third treatment group, also referred to as the *joint treatment*, are exposed to both vacancy information (A) and occupational recommendations (B).

2.3 Treatment assignment

To study the potential impact of treatment spillovers, we adopted a two-stage randomized trial design, in which treatment assignments were varied both at the individual and regional levels (see also Crépon *et al.*, 2013; Baird *et al.*, 2018). In the first stage, we randomly distributed each of the 98 Danish municipalities into one of three distinct regimes: super-control, 60%-assignment, and 90%-assignment. To ensure that regions with different assignment probabilities exhibited similar characteristics, we implemented a stratified randomized design in this first stage. To that end, we created ten groups of municipalities that exhibit similar local labor market characteristics, such as local unemployment rate, labor market tightness, and the distribution of education and age among the local population. Within each of these ten strata, municipalities are subsequently assigned randomly to the three different assignment regimes.

Table 2: Overview of two-stage randomized trial design

		Treatment weights				
Assignment regime	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

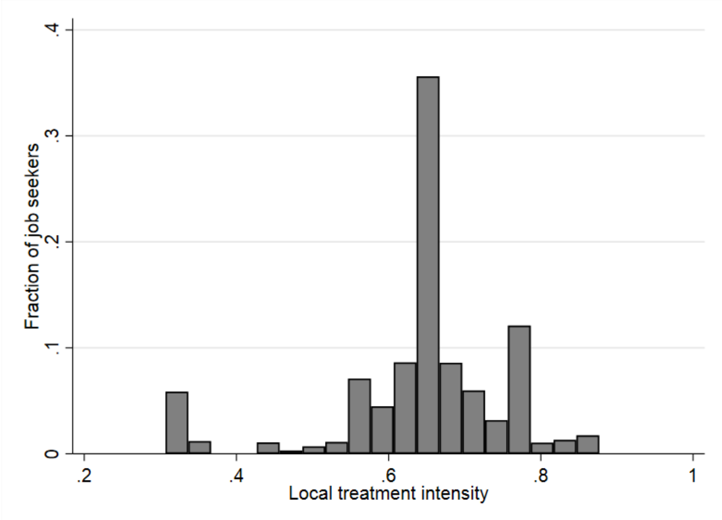
Note: The table summarizes the two-stage randomized controlled trial design. Column (2) illustrates the number of municipalities within each of the three assignment regime, while columns (3)–(6) depicts the share of job seekers assigned to each of the four treatment arms.

In the second stage of randomization, we allocated each job seeker to different treatment arms based on the assignment regime associated with their place of residence. In ten municipalities, all unemployed workers were assigned exclusively to the control group. In all other municipalities, unemployed workers were randomly assigned to either the control group or one of the three treatment groups (recommendation treatment, vacancy treatment, or joint treatment). Specifically, in 44 municipalities, job seekers had a 40% probability of being assigned to the control group, and a 20% probability of being assigned to each of the three information treatments. In the remaining 44 municipalities, job seekers had a 30% probability of being assigned to each of the three treatments, while 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 random assignment of individuals to the four treatment groups within each municipality.

The identification of treatment spillovers builds on the notion of “self-contained” local labor markets, which exhibit variation in the proportion of treated individuals. That said, it is clear that job seekers may not confine their search activities solely to their own municipality. Therefore, in our empirical analysis in Section 5, we leverage the variation in assignment probabilities at the municipality-level to construct a continuous measure of treatment intensity. To achieve this, we analyze the commuting patterns of all Danish workers among the 98 municipalities in the three years preceding our experiment. Based on the resulting commuting matrix, we calculate the local treatment intensity (TI_j) for each municipality by considering the share of treated individuals in all other municipalities, weighted by the corresponding proportion of commuters between any pair of municipalities. This measure serves as a proxy for the extent to which job seekers are exposed to other treated individuals searching for employment within the same local labor market.

As shown in Figure 1, our two-stage randomization procedure creates substantial variation with respect to the share of treated individuals within a local labor market. While the median job seeker is exposed to a treatment intensity of 65%, we observe a range of variation between 30% and 86%. Therefore, our empirical analysis of spillover effects can utilize data from local labor markets where job seekers have relatively little exposure to other treated individuals, as well as markets where the intervention has been implemented almost universally. Moreover, as we will further discuss in Section 5.2, we examine the robustness of our findings with respect to various alternative definitions of local labor markets and intensity measures.

Figure 1: Distribution of local treatment intensity



Note: Depicted is the local treatment intensity (TI_j) calculated for each of the 98 Danish municipalities. The measure is derived from the proportion of treated individuals in all other municipalities, weighted by the corresponding proportion of commuters between any pair of municipalities.

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.*, 2023). 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: 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.

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. To begin with, we outline how vacancy information and occupational recommendations may affect the search behavior unemployed workers in a partial-equilibrium framework. In the spirit of, for instance, Belot *et al.* (2019), job seekers can direct their search effort towards different occupations, while they face uncertainty about their job finding prospects in the various occupations. Afterwards, we illustrate how potential treatment externalities may impact the matching process at the aggregate level (see also Kircher, 2022).

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 and the value of employment is denoted by V.

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

$$\rho U = \max_{s_1,\ldots,s_K} \left[b - \gamma(s) + \left\{ 1 - \prod_k (1 - \widehat{\lambda}_k(s_k)) \right\} (V - U) \right] \tag{1}$$

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. The optimal allocation of search effort across occupations depends on the job seeker's relative perceived returns to search, $\widehat{\lambda}'_k$, across the various occupations.

3.2 Potential effects of search advice on job seekers' behavior

To illustrate the potential effects of occupational recommendations and vacancy information it is useful to distinguish between two classes of occupations. For their "core" occupations, job seekers' subjective belief about the job offer arrival rate is sufficiently high, prompting them to include these occupations in their personal search profile prior to the intervention. In contrast, job seekers' subjective belief concerning the job offer arrival rate in other "non-core" occupations is lower, leading them to exclude these occupations from their initial 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.[6]

Occupational recommendations: Receiving a recommendation regarding an occupation k should increase job seekers' perceived returns to search in the recommended occupation. Our algorithm exclusively recommends non-core occupations that have not been included in the initial search profile. Consequently, receiving a recommendation should encourage individuals to exert relatively more effort searching for a job in recommended non-core occupations. Moreover, 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, intensifying their search efforts in recommended occupations may entail a trade-off, potentially leading to reduced search activities in other occupations, including the core occupations initially included in the search profile. The effectiveness of such a modified search strategy in enhancing labor market outcomes hinges on the actual prospects in the various occupations, $\lambda_k(s_k)$. For instance, occupational recommendations may yield greater benefits for job seekers who initially contemplate occupations with relatively unfavorable conditions (e.g. those with limited vacancies) in comparison to the occupations suggested by our algorithm.

Vacancy information: In contrast to occupational recommendations, the vacancy information relates to the occupations already included job seekers' search profile, and as such, it should influence their beliefs regarding these core occupations. Notably, there exists a strong positive correlation ($\rho = 0.52$) between the quantity of job vacancies presented to treated individuals and the associated labor market tightness (i.e. posted vacancies relative to job seekers). Hence, depending on their prior beliefs, the vacancy information may affect job seekers' perceived re-

[6]Empirically, we observe that job seekers direct approximately 53% of their applications to core occupations stored in their personal job search profile.

turns to search in their core occupation. For example, they might be positively surprised by the number of vacancies in their core occupations and may conclude that the returns to search are larger than expected (e.g., if some or all of the core occupations are in particularly high demand). In this case, job seekers might redirect their search efforts from non-core to core occupations. If this shift is strong enough, individuals may narrow down the range of occupations they explore. Conversely, we anticipate 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 how individuals interpret the vacancy information, whether as a negative or positive signal, and on the actual prospects within their core occupations. For instance, if job seekers' perceive the vacancy information as a positive surprise and the labor market conditions in their core occupations are relatively favorable, concentrating their search efforts on core occupations may entail positive employment effects.

3.3 Aggregate effects and externalities of job search advice

The partial-equilibrium model implicitly assumes that if some job seekers increase their search effort in a certain occupation the extra labor supply in that occupation is absorbed by the creation of additional employment. That is, the information provided through the dashboard impacts the job seekers' subjective beliefs about the labor market prospect in the various occupations, $\widehat{\lambda}_k(s_k)$, but not their actual labor market prospects, $\lambda_k(\cdot)$. In reality, however, job creation may not fully adjust such that changes to an individual's search behavior have externalities on other job seekers.

As highlighted by Kircher (2022), offering search advice can enhance efficiency and increase aggregate employment by redirecting workers from markets with relatively few vacancies to markets with a higher abundance of job opportunities. To illustrate this, it is instructive to consider the number of job matches that occur in a specific occupation k, $m(u_k, v_k)$. Following the standard matching model (see, e.g., Pissarides, 2000; Michaillat, 2012; Crépon *et al.*, 2013), the matching function $m(\cdot)$ is increasing and concave in the number of posted vacancies, v_k, and the total effort exercised by the unemployed searching for jobs in occupation k, u_k. The occupation-specific conditions are summarized by the labor market tightness $\theta_k = v_k/u_k$. Given this, we can denote the probability that a job seeker exercising search effort s_k finds a job in occupation k by:

$$\lambda_k = \phi_k s_k m(u_k, v_k)/u_k = \phi_k s_k m(\theta_k). \tag{2}$$

where ϕ_k denotes the search efficiency capturing, for example, how well job seekers' skills align with the job requirements of a particular occupation k. Notice that, in contrast to the partial-equilibrium setting, job seekers' prospects in occupation k are not only influenced by their own effort choices but also by the occupation-specific tightness, θ_k, capturing the decisions of all other job seekers.

A social planner, who wants to maximize the overall number of matches in the economy, would optimally allocate each job seeker's search effort across different occupations such that their marginal contribution to the hiring process is balanced across occupations (see Şahin *et al.*, 2014). This can be illustrated by the following rule:

$$\phi_1 s_1 m'_{u_1}(\theta_1) = ... = \phi_k s_k m'_{u_k}(\theta_k) = ... = \phi_K s_K m'_{u_K}(\theta_K), \quad (3)$$

where m'_{u_k} denotes the derivative of the occupation-specific matching function with respect to u_k. Equation (3) characterizes the optimal allocation of search effort across occupations for each individual. In situations where this condition is not met, redirecting job seekers' search activities has the potential to effectively increase the overall number of job matches. For instance, this might be the case when the initial tightness varies significantly across different occupations. In such scenarios, both treated and non-treated individuals can benefit. Treated job seekers may experience improved employment prospects as they adapt their job search strategies, targeting occupations with a higher likelihood of a successful match. Meanwhile, non-treated individuals may also benefit as they now seek jobs in occupations that become relatively less competitive, that is, θ_k increases.

However, there is a risk that providing search advice may lead to congestion effects if an excessive number of job seekers are prompted to apply for the same vacancies, which could reduce efficiency and overall employment levels. In such a scenario, certain occupations may become overly congested, leading to a decrease in tightness and reducing the returns to search within those occupations. This comes at the expense of non-treated individuals searching for jobs in those occupations in absence of the intervention. Moreover, it induces negative treatment spillovers on treated individuals, for instance, if they do not take into account that others are receiving similar information (see e.g. Ferracci *et al.*, 2014). In our setting, the advice that job seekers receive is customized based on their individual job search profiles. This means that treated individuals with similar profiles also receive the same kind of advice. Therefore, it is conceivable that congestion effects diminish the effectiveness of search advice and reduce aggregate employment when the share of treated individuals approaches a full roll-out.

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.* (2023) suggests that the data are informative on how job seekers allocate their applications across occupations.[7]

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:

$$Y_i = D_i\mu + X_i\beta_1 + \varepsilon_i. \tag{4}$$

where D_i is a vector indicating whether individuals were assigned to 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). 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. 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.

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

[7] 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	Fraction recom. occupations$^{(a)}$ (1)	Fraction core occupations$^{(b)}$ (2)	Fraction distinct occupations$^{(c)}$ (3)	Avg. labor market tightness$^{(d)}$ (4)
	Registered job applications within four weeks			
Treatment status (ref. control group)				
Recommendation treatment (μ^R)	0.0063**	-0.0085***	0.0035	0.0114***
	(0.0030)	(0.0033)	(0.0023)	(0.0039)
Vacancy treatment (μ^V)	-0.0015	0.0082**	-0.0062***	0.0101***
	(0.0030)	(0.0033)	(0.0023)	(0.0039)
Joint treatment (μ^J)	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 control group	0.265	0.526	0.500	0.136
Control variables	Yes	Yes	Yes	Yes

Note: The table reports treatment differences (relative to the control group) 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 applications in non-core occupations that were/would have been recommended by the algorithm.
$^{(b)}$Share of registered applications in core occupations included in job seekers' search profile in the week prior to the start of the intervention.
$^{(c)}$Number of registered job applications in 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 included the corresponding occupation in their search profile relative to the number of available vacancies in the week prior to the start of the intervention.

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 included in their personal job search profile at the beginning of the intervention, by about 1.6% ($p = 0.010$; see column 2). These effects align with the notion that occupational recommendations increase job seekers' perceived returns to search in the recommended occupations.[8] 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 in column (4) suggest that—in absence of treatment externalities—the altered search strategy has the potential to improve job seekers' reemployment prospects. To be specific, treated individuals tend to focus their search activities on occupations with a higher labor market tightness, i.e., occupations with a higher number of vacancies per job seeker. On average, individuals assigned to the recommendation

[8]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.

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.[9]

Vacancy treatment: In contrast to occupational recommendations, the vacancy treatment increases the fraction of applications sent to job seekers' core occupations included in their search profile initially (see column 2). Relative to the control group, we find an increase of approximately 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. This, in turn, encourages them to focus their search activities on these occupations. Notably, as depicted in column (4), the adjusted search strategy is also associated with a rise in the average labor market tightness within the occupations where job seekers apply (+7.4%; $p = 0.005$). The magnitude of this effect closely resembles the corresponding impact of the recommendation treatment.

Joint treatment: Lastly, when examining the portfolio of job applications among job seekers in the joint treatment, differences with respect to the control group are less pronounced than those observed for the recommendation and the vacancy treatments, respectively. This finding may not come as a surprise, as the joint treatment combines both occupational recommendations and vacancy information, which appear to elicit opposing behavioral responses from job seekers (i.e., a broadening of job search strategy in response to occupational recommendations and a narrowing down in response to vacancy information). Nonetheless, we also note that individuals in the joint treatment apply to occupations with a labor market tightness that is 7.4% higher ($p = 0.005$) compared to 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 components appear 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 taking into account potential externalities in Section 5.2, we first compare the average labor market outcomes of treated and non-treated job seekers in Section 5.1. Moreover, we study heterogeneous treatment effects with respect to the elapsed

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

unemployment duration and the occupation-specific labor market conditions in Section 5.3. Lastly, we examine consequences for aggregate levels of employment and earnings in Section 5.4.

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

We commence our analysis by providing "naive" estimates of the labor market effects of online job search advice. These estimates compare the average employment outcomes of treated and non-treated job seekers in the overall sample. While this aligns with the approach adopted by numerous studies analyzing randomized trials, it ignores potential externalities of job search advice. Figure 2 illustrates treatment differences (estimated based on Equation (4)) in job finding rates, total working hours, and total labor earnings in comparison to the control group for various time periods.

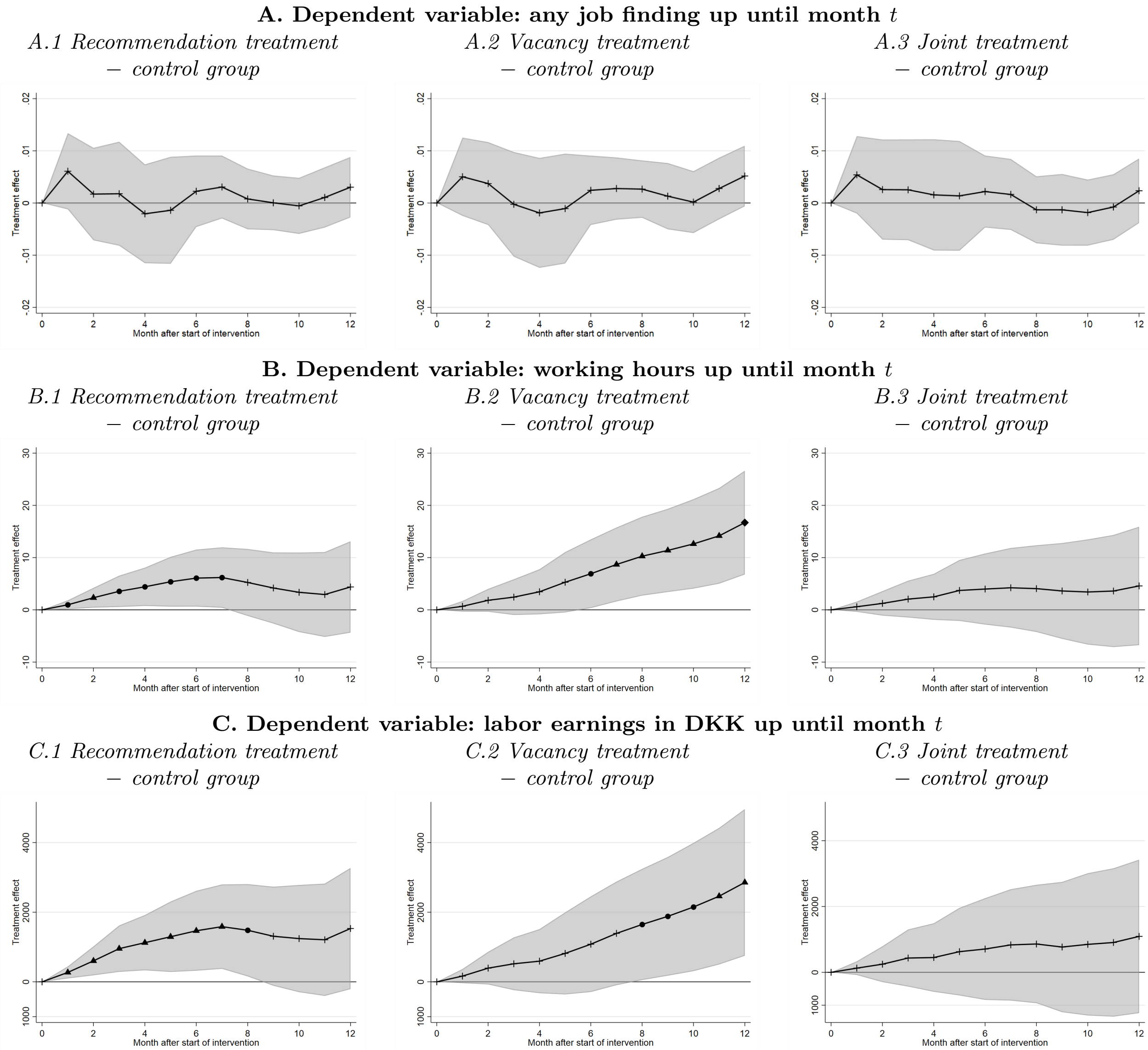
While the naive estimates do not provide any indications that the three treatments influence job finding rates (see Panel A of Figure 2), both the recommendation and vacancy treatments do exert a significant impact on total working hours and earnings. In the short term, individuals assigned to the recommendation treatment work more hours and obtain higher earnings compared to the control group. Within the first six months of the experiment, the differences accumulate to around 6.1 additional hours worked ($p = 0.068$; see Panel B.1) and DKK1,467 in labor earnings ($p = 0.037$; see Panel C.1). These figures represent relative effects of 1.8% and 2.4%, respectively, when compared to the average outcomes of the control group. The initial positive impact of the recommendation treatment gradually diminishes over time, to the extent that we only observe statistically insignificant differences when analyzing average outcomes over the first 12 months following the start of the intervention.

Moreover, job seekers assigned to the vacancy treatment also experience an increase in working hours and earnings compared to the control group. However, unlike the recommendation treatment, this difference progressively amplifies over time. After 12 months, individuals in the vacancy treatment work approximately 16.8 additional hours ($p = 0.007$; see Panel B.2) and earn DKK2,684 more ($p = 0.028$; see Panel C.2) than those in the control group, reflecting relative increases of 2.2% and 1.9%, respectively. Finally, when examining the joint treatment, encompassing both occupational recommendations and vacancy information, our naive estimates do not reveal any statistically significant differences compared to the control group.

5.2 The direct and indirect effects of online job search advice

The estimates presented in the previous section do not account for externalities that may arise when individuals modify their search strategy in response to the advice they receive, potentially

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



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.

altering the competition across occupations. In the presence of spillovers, comparing mean outcomes across treatment groups does not isolate the direct impact of job search advice. Instead, it combines the direct effect without the influence of treated peers and the difference in weighted averages of spillover effects among treated and non-treated individuals (Vazquez-Bare, 2022).

5.2.1 Econometric specification

To examine the relevance of such externalities, we leverage the exogenously induced variation in treatment intensities across municipalities. If there are no treatment spillovers, the labor market outcomes of both treated and non-treated individuals should be independent of the local treatment intensity. However, as outlined in Section 3.3, the presence of spillover effects can result in either positive or negative externalities, contingent on how the intervention alters the competition among job seekers across occupations.

We estimate interacted regression in the spirit of Crépon *et al.* (2013):

$$Y_{ij} = D_i\alpha + TI_j\gamma + (D_i \times TI_j)\delta + X_i\beta + \varepsilon_{ij}, \tag{5}$$

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 in municipality j as illustrated in Figure 1. Again, X_i captures a vector of control variables including dummies for the ten market strata used for randomization at the municipality level.

In this setting, the set of coefficients denoted by α approximate the direct treatment effects 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. In our main specification, we consider the continuous treatment intensity as depicted in Figure 1. Additionally, we use the continuous measures to define indicator variables identifying regions with treatment intensities in the bottom, middle and top tercile of the distribution 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 Validity of empirical approach

The identification of spillover effects hinges on the assumption that treatment intensities are uncorrelated with potentially confounding factors. As described in Section 2.3, we randomly allocated each of the 98 municipalities to the three assignment regimes to ensure that the share of treated job seekers is exogenous. At the same time, we empirically examine the validity of this assumption in several ways.

First, we test to what extent individual characteristics observed in our data are correlated with the treatment intensity measure. As shown in Table A.1, regional differences with respect to individual characteristics have little explanatory power (see $p-$values at bottom of Table A.1).

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.1). 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.

Second, we consider a placebo sample including 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 local treatment intensity is correlated with labor market outcomes of individuals who were not exposed to the experiment. As demonstrated in Table A.2, there is no statistically significant relationship between the treatment intensity and the labor market outcomes of the placebo sample. This supports the assumption that regions with varying treatment intensities are similar regarding other relevant factors affecting job seekers' labor market outcomes.

Third, we examine the sensitivity of our results with respect to the inclusion of different control variables in our regression models. Given that Equation (5), identifies heterogeneous treatment effects for job seekers who are exposed to different levels of treatment intensities, we additionally account for interaction terms of the treatment status and the treatment intensity with all individual characteristics included in our regression model. This enables us to test whether the estimated coefficients (α, γ and δ) change when accounting for other dimensions of heterogeneous effects, such as individual-level differences that may not be fully balanced across regions. The results are presented in Table A.3 in the Appendix and they turn out to be very robust across the different specification tests.

Lastly, we explore how the definition of local labor markets exhibiting variation in the proportion of treated individuals affects our estimation results. While our main analysis relies on the share of treated job seekers among all municipalities weighted by municipality-specific commuting flows, we test the robustness of our findings for five alternative definitions of local treatment intensities. Specifically, we (i) use the fraction of treated individuals within job seeker's own municipality and all bordering municipalities, (ii) account for differences in the share of treated searching within the same occupations, (iii) consider larger administrative areas (i.e. the share of treated within the 11 Danish provinces), (iv) only use the three most popular commuting destinations and (v) take into consideration job seekers' actual applications in the past. We further discuss the exact definitions of local labor markets in Section A.2 in the Appendix. Table A.4 compares the estimated coefficients for the different intensity measures. Most importantly, all specifications reveal very similar patterns, which is reassuring for the validity of our approach.

5.2.3 Direct and indirect treatment effects

We proceed by examining the direct and indirect effects of search advice, estimated based on Equation (5), on the three main outcomes: (1) the job finding probability, (2) total working hours and (3) total labor earnings measured within 12 months after the start of the intervention. Notably, the labor market impacts of online job search advice are significantly influenced by the proportion of treated individuals within a given region.

Upon analyzing the continuous treatment intensity measure (see columns 1–3), we observe that the α-coefficients, which approximate the direct effects of job search advice when the proportion of other treated individuals is low, exhibit positive values for all three treatments. More specifically, our estimates suggest that both the recommendation and vacancy treatments significantly increase overall working hours and labor earnings when the number of other treated individuals approaches zero (see α^R and α^V in columns 2 and 3, respectively). Notably, we also estimate positive effects from the joint treatment, but its impact is statistically insignificant and tend to be smaller than for the recommendation and vacancy treatments. This suggests that vacancy information and occupational recommendations do not "add up" when being combined.

When considering treatment spillovers, we do not find any evidence suggesting that non-treated job seekers are affected by a larger share of treated individuals. The estimated γ-coefficients are relatively small and lack statistical significance. However, at the same time, the proportion of treated individuals within a local labor market appears to play a crucial for the outcomes of individuals who receive search advice. As indicated by the negative interaction effects, higher treatment intensities significantly reduce working hours and labor earnings of job seekers who are assigned to the recommendation and vacancy treatments. For instance, the estimates in column (3) suggest that raising the treatment intensity by ten percentage points reduces the effect of the recommendation treatment on labor earnings by DKK2,356 [$= 0.1 \times (1,783 - 25,346)$], which reflects an earnings reduction of about 1.6% relative to the sample mean. While the corresponding estimates of the negative indirect effects for the vacancy treatment are very similar in magnitude, we estimate smaller and insignificant coefficients for the joint treatment.[10]

When exploring the categorical intensity measure (see columns 4-6 of Table 5), we do not observe any compelling evidence suggesting strong non-linearities in the indirect effects of our treatments. As also visualized in Figure 3, within the bottom tercile of the treatment intensity

[10] One should note that the magnitudes of the estimated effects vary somewhat for the different treatment intensity measures analyzed in Table A.4. However, our observation that the labor market effects of the joint treatment are less pronounced than for the recommendation and vacancy treatments turns out to be robust across the various specifications.

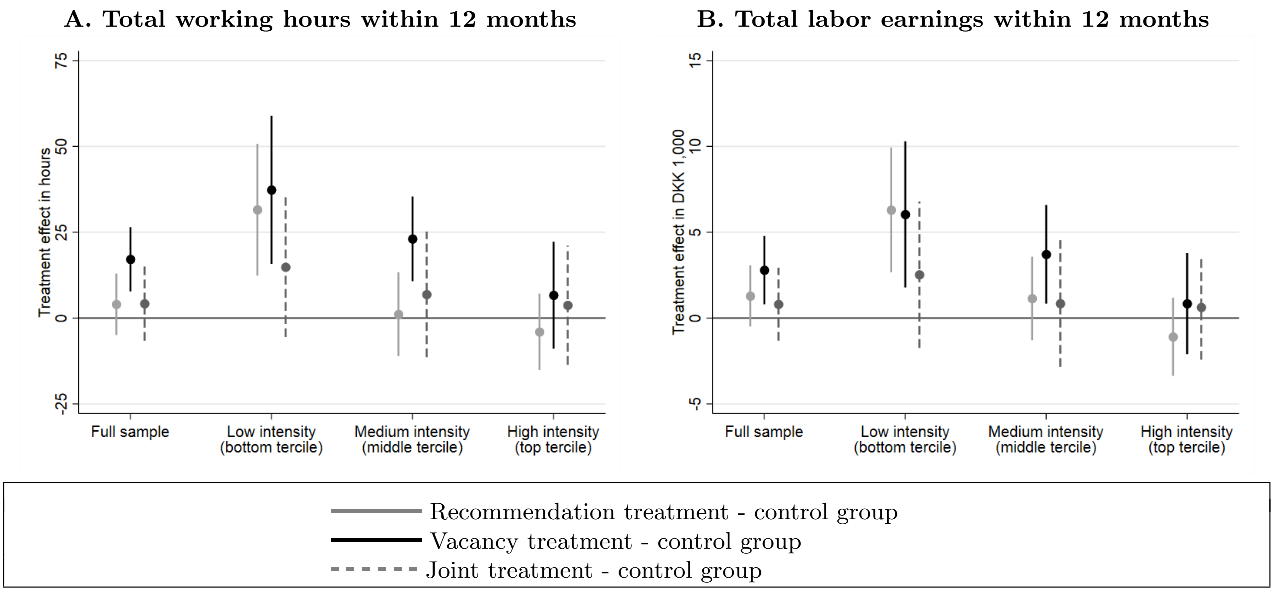
Table 5: Direct and indirect treatment effects on labor market outcomes

	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 (in DKK)	Labor earnings	Any job finding	Working hours (in DKK)	Labor earnings
	(1)	(2)	(3)	(4)	(5)	(6)
Recommendation treatment (α^R)	0.036*	72.1**	18,222**	0.010	31.3***	6,428***
	(0.021)	(35.0)	(8,264)	(0.007)	(11.0)	(2,131)
Vacancy treatment (α^V)	0.036	93.2**	19,577**	0.016**	36.2***	6,013**
	(0.026)	(37.5)	(8,301)	(0.008)	(11.3)	(2,293)
Joint treatment (α^J)	0.037	46.0	11,427	0.011	14.6	2,656
	(0.026)	(43.3)	(8,551)	(0.008)	(12.1)	(2,546)
Local treatment intensity (γ_{cont})[c]	0.003	-19.8	1,783			
	(0.015)	(23.2)	(4,619)			
× Recommendation treatment (δ^R_{cont})	-0.048	-100.5*	-25,346**			
	(0.032)	(52.2)	(12,301)			
× Vacancy treatment (δ^V_{cont})	-0.046	-112.5**	-25,112**			
	(0.038)	(55.4)	(12,388)			
× Joint treatment (δ^J_{cont})	-0.051	-61.5	-15,946			
	(0.041)	(64.7)	(12,715)			
Local treatment intensity (ref. low intensity)[b]						
Medium intensity (γ_{med})				-0.006	-19.6	716
				(0.008)	(15.2)	(3,411)
× Recommendation treatment (δ^R_{med})				0.001	-30.0**	-5,442**
				(0.010)	(13.5)	(2,484)
× Vacancy treatment (δ^V_{med})				-0.014	-14.5	-2,752
				(0.009)	(13.4)	(2,936)
× Joint treatment (δ^J_{med})				-0.007	-9.9	-2,347
				(0.010)	(16.1)	(3,349)
High intensity (γ_{high})				0.006	-0.6	203
				(0.009)	(13.0)	(1,850)
× Recommendation treatment (δ^R_{high})				-0.019*	-42.8***	-8,210***
				(0.011)	(14.5)	(2,729)
× Vacancy treatment (δ^V_{high})				-0.016	-36.3**	-5,780*
				(0.011)	(16.0)	(3,035)
× Joint treatment (δ^J_{high})				-0.017	-17.7	-2,664
				(0.012)	(17.0)	(3,285)
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				0.489	0.422	0.975
Recommendation treatment				0.080	0.013	0.013
Vacancy treatment				0.258	0.077	0.165
Joint treatment				0.352	0.576	0.684

Note: The table reports the results of interacted regressions of treatment indicators and local treatment intensities as described by 5 estimated for the full experimental population. In all specifications, we control for individual characteristics as depicted in Table 3 and dummies for ten market strata. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level. The dependent variables refer to overall job finding rates, respectively accumulated working hours and labor earnings over a period of 12 months after the start of the intervention.
[a] Continuous treatment intensity as depicted in Figure 1.
[b] Categorical variable with indicators for low (bottom tercile), medium (middle tercile) and high (top tercile) treatment intensities.

distribution, both job seekers assigned to the occupational recommendation and vacancy information treatment experience a significant increase of 4.0–4.5% in overall working hours and labor earnings compared to the control group. However, in regions characterized by intermediate treatment intensity (i.e., in the middle tercile of the distribution), the effects observed are notably smaller. Here, the impacts of the recommendation and joint treatments appear to be close to zero and lack statistical significance. Only individuals assigned to the vacancy treatment exhibit a significant increase in working hours (+3.1%; $p = 0.006$) and higher earnings (+2.9%; $p = 0.047$), but it is noteworthy that the effects of the vacancy treatment in these intermediate-intensity regions are approximately 40% smaller than those observed in low-intensity regions. Finally, as we approach a full roll-out, the effects of all three treatments are entirely washed away. In regions within the top tercile of treatment intensities, none of the three treatment groups demonstrates higher levels of employment or earnings compared to the control group.

Figure 3: Treatment differences 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. In all specifications, we control for individual characteristics as depicted in Table 3 and dummies for ten market strata. Standard errors are clustered at the municipality level.

5.2.4 Crowding out of job seekers

The findings from the previous section demonstrate that exposing a larger share of individuals to online job search advice leads to a decline in the labor market performance of treated job seekers. A plausible explanation for this pattern is that treated job seekers, who alter their search behavior in response to the intervention, tend to concentrate their efforts on the same labor markets. This increased concentration of applications towards specific jobs may result in congestion effects, ultimately hindering their labor market integration.

In the following, we explore the relevance of this mechanism by analyzing the number of job applications per vacancy. While the data on registered applications from the online portal do not allow us to precisely measure the degree of competition 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 calculate 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.[11] With these measures as the dependent variables, we proceed to re-estimate the regression characterized by Equation (5). This approach allows us to shed light on the changes in occupation-specific competition faced by both treated and non-treated job seekers under different treatment intensities.

Table 6: Crowding out of job seekers among occupations

Dependent variable	Average no. of applications per vacancy in occupations applied to$^{(a)}$	
	within four weeks	within 12 months
	(1)	(2)
Recommendation treatment (α^R)	-24.9**	-25.3
	(11.3)	(32.1)
Vacancy treatment (α^V)	-24.1**	-31.9
	(11.3)	(34.2)
Joint treatment (α^J)	-26.2**	-30.7
	(11.3)	(30.3)
Local treatment intensity (γ_{cont})$^{(b)}$	-33.3**	-76.0***
	(14.3)	(22.1)
× Recommendation treatment (δ^R_{cont})	39.7**	47.9
	(17.4)	(49.7)
× Vacancy treatment (δ^V_{cont})	37.7**	57.2
	(17.4)	(53.2)
× Joint treatment (δ^J_{cont})	41.3**	57.1
	(17.5)	(47.5)
No. of observations	92,098	92,098
Mean value dep. variable	40.5	155.2

Note: The table reports the results of interacted regressions of treatment indicators and local treatment intensities (continuous measure) as described by Equation 5 estimated for the full experimental population. In all specifications, we control for individual characteristics as depicted in Table 3 and dummies for ten market strata. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level.
$^{(a)}$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.

Column (1) of Table 6 shows the corresponding estimates based on the continuous measure of treatment intensity when considering all applications registered within the first four weeks after

[11] Note that the occupational-specific labor market tightness analyzed in Section 4 measures the competition in a particular occupation in the pre-intervention period. Conversely, in the current analysis, we now analyze the competition across occupations after treated individuals have been exposed to job search advice.

the start of the intervention. The findings align with the notion that the negative externalities on treated job seekers are indeed provoked by changes in the degree of competition across occupations. When treatment intensities are low, treated job seekers in all three treatment arms tend to apply to occupations where they face significantly less competition than non-treated individuals. 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 observe a negative γ-coefficient suggesting that the control group experiences reduced competition when the treatment intensity increases. This finding aligns with the idea that treated job seekers tend to apply to occupations distinct from those pursued by non-treated individuals. However, despite the eased competition in response to higher treatment intensities, we do not observe improved employment outcomes among job seekers assigned to the control group when the proportion of treated job seekers increases. A potential reason for the absence of positive spillovers on the labor market integration of non-treated could be that predominately longer-term unemployed with low reemployment prospects alter their search behavior in response to our intervention (see, e.g., Belot *et al.*, 2019, for a theorectical discussion and empirical evidence). Therefore, the reduced competition may not necessarily raise employment and earnings of the average job seeker in the control group. We further explore this idea in Section 5.3, where we show that our intervention also has stronger effects on job seekers who are already unemployed for longer periods.

Additionally, and perhaps most importantly, the results from Table 6 reveal that the effects on applicant competition in the occupations targeted by treated job seekers reverse as the treatment intensity increases. Treated individuals in regions with higher treatment intensities tend to apply to occupations with greater competition, i.e., a higher number of applications per vacancy. This finding suggests that the negative treatment spillovers on unemployed workers receiving advice are indeed triggered by crowding out among treated job seekers. As more and more individuals alter their job search strategy in response to the intervention, they eventually target similar occupations, leading to congestion within those labor markets.

Finally, when examining the effects on applications within the first 12 months after the start of the intervention (see column 2 of Table 6), the overall pattern appears similar, but the coefficients become smaller (relative to the sample mean) and mostly insignificant. A plausible explanation for this finding is that job seekers react to the increased competition by (re-)adjusting their application behavior over time.

5.3 Who benefits from online job search advice?

Given that both, occupational recommendations and vacancy information, 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. Therefore, we now 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 included in job seekers' initial 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 policymakers. For our empirical analysis, we divide the experimental sample at the median of the two variables and estimate Equation (5) for the different subgroups.

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), 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 Table 7, all three treatments tend to have 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 joint treatment. These findings indicate that long-term unemployed job seekers benefit from online job search advice to a 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.

Table 7: Subgroup analysis by elapsed unemployment duration and labor market tightness

Dependent variable	A. By elapsed unemployment duration				B. By labor market tightness			
	Working hours within 12 months		Labor earnings (in DKK) within 12 months		Working hours within 12 months		Labor earnings (in DKK) within 12 months	
	Short UE duration (< median)	Long UE duration (≥ median)	Short UE duration (< median)	Long UE duration (≥ median)	Low tightness (< median)	High tightness (≥ median)	Low tightness (< median)	High tightness (≥ median)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Recommendation treatment (α^R)	68.1	149.1***	17,588	28,634***	127.3**	63.1	24,975**	16,099
	(53.4)	(54.3)	(11,065)	(8,935)	(57.5)	(55.1)	(9,569)	(11,248)
Vacancy treatment (α^V)	91.8*	154.3**	14,731	30,041**	88.1	141.3***	20,102*	19,910**
	(51.8)	(64.8)	(11,342)	(11,561)	(54.3)	(51.4)	(10,326)	(9,571)
Joint treatment (α^J)	25.7	149.4**	4,766	28,789**	68.2	80.7*	13,368	14,630
	(52.0)	(60.6)	(9,955)	(11,151)	(57.2)	(45.1)	(9,603)	(9,047)
Local treatment intensity (γ_{cont})$^{(a)}$	-32.9	8.5	1,506	7,982	-19.1	-79.9*	4,837	-11,914*
	(33.4)	(58.8)	(5,315)	(9,804)	(43.3)	(41.5)	(6,867)	(6,055)
× Recommendation treatment (δ^R_{cont})	-96.6	-211.2**	-23,735	-41,876***	-185.7**	-83.7	-36,094**	-22,144
	(80.1)	(81.6)	(16,526)	(13,278)	(86.5)	(82.2)	(14,658)	(16,237)
× Vacancy treatment (δ^V_{cont})	-116.3	-200.0**	-18,294	-41,907**	-98.5	-189.6**	-25,441*	-26,935*
	(77.2)	(96.1)	(17,272)	(16,744)	(81.8)	(77.0)	(15,311)	(13,871)
× Joint treatment (δ^J_{cont})	-40.3	-206.8**	-7,262	-41,393**	-94.1	-111.0	-19,679	-20,103
	(77.2)	(89.1)	(14,562)	(16,023)	(86.0)	(68.2)	(14,110)	(13,096)
No. of observations	45,944	46,154	45,944	46,154	46,049	46,049	46,049	46,049
Mean value dep. variable	879.5	710.6	165,252	127,360	762.2	841.1	137,784	158,236

Note: The table reports the results of interacted regressions of treatment indicators and local treatment intensities (continuous measure) as described by Equation 5 estimated for the full experimental population. In all specifications, we control for individual characteristics as depicted in Table 3 and dummies for ten market strata. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level. The dependent variables refer to accumulated working hours and labor earnings over a period of 12 months after the start of the intervention.

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

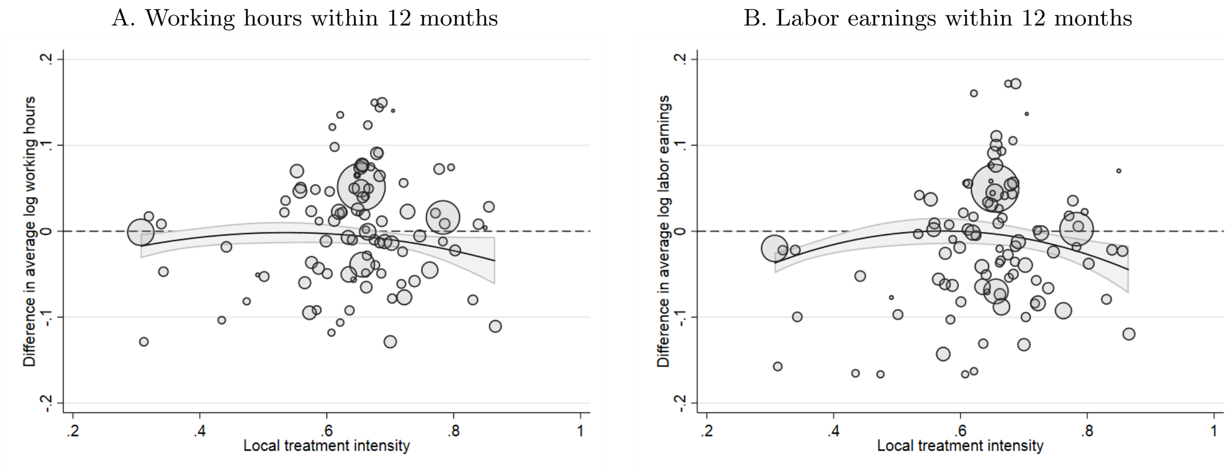
Labor market tightness: As a second dimension of heterogeneity, we consider the labor market tightness in job seekers' core occupations included in their initial search profile—an indicator of how difficult it is for a given job seeker to find a job in absence of the intervention. Since the expected 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 anticipate 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 Table 7 support these ideas. The positive direct effects of the recommendation treatment are substantially larger for job seekers with a personal search profile that is characterized by low labor market tightness. Conversely, the positive employment effect of the vacancy treatment more pronounced among those who face relatively good job prospects in the set of occupations stored in their personal job search profile.

The observed heterogeneity of the treatment effects in regions with low treatment intensity aligns 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 envision that a more targeted provision of job search advice, tailored to specific groups of job seekers who benefit most strongly from a particular form of advice, might enhance welfare by reducing negative spillovers. However, it is equally crucial to gain a deeper understanding of which job seekers actually compete with each other to determine the optimal degree of personalization, while also accounting for the indirect effects of online job search advice on other job seekers.

5.4 Aggregate effects of job search advice

In the final step of our empirical analysis, we study how the share of treated individuals relates to aggregate levels of employment and earnings. In relation to our discussion of potential spillover effects in section 3.3, this provides insights into the optimal proportion of job seekers' receiving search advice from the perspective of a planner who aims at maximizing overall matching efficiency. On the one hand, providing search advice to some job seekers is beneficial because it redirects workers from markets with relatively few vacancies to markets with abundant job opportunities. On the other hand, when approaching a full roll-out, congestion effects reduce the overall matching efficiency.

Figure 4: Aggregate labor market outcomes by local treatment intensity



Note: The figure depicts a weighted scatterplot illustrating log differences in overall working hours (Panel A) and labor earnings (Panel B) between the experimental sample and the placebo sample aggregated at the municipality level (y-axis) in relation to local treatment intensities (x-axis). The size of the dots represents weights, indicating the number of unemployed workers per municipality in the experimental sample. Additionally, the figure shows a quadratic fit for the depicted relationships, including 90% confidence intervals. Table A.5 in the Appendix presents the results of the corresponding quadratic regressions.

With this in mind, we now investigate the relationship between the local treatment intensity and the average labor market outcomes at the municipality level. To be specific, we consider changes in employment and earnings at the municipal level between the experimental sample, where treated individuals received search advice, and the placebo sample, including the stock of UI benefit recipients one year before the start of the experiment.[12] Thereby, we examine how the roll-out of our intervention has impacted the aggregate outcomes of unemployed workers in regions with different treatment intensities.

Figure 4 depicts a weighted scatterplot of log changes in average working hours (Panel A) and labor earnings (Panel B) in relation to local treatment intensities (with weights corresponding to the number of job seekers per municipality), along with a quadratic fit.[13] Positive values indicate improved labor market prospects for job seekers in the respective municipality compared to the pre-intervention year, while negative values suggest a decline in their prospects. The estimated inverted U-shape, which is particularly pronounced for labor earnings (see Panel B of Figure 4), indicates that the provision of job search advice maximizes aggregate outcomes at intermediate levels of treatment intensity. However, as the proportion of treated individuals increases further, aggregate outcomes tend to decline. This reiterates the importance of negative spillovers, likely

[12]For the placebo sample, we consider the stock of unemployed workers as of March 2018 and the outcomes of this sample are measured over the period between March 2018 and February 2019, that is, the 12-month period just before the start of the experiment.

[13]Table A.5 shows the results of the quadratic regressions underlying the illustration in Figure 4.

due to congestion effects that reduce matching efficiency when approaching a full roll-out of our intervention.

6 Conclusion

Offering job search advice is a key policy for reintegrating unemployed workers into the labor market. In this context, the use of digital tools bears great promises—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, offering both types of advice simultaneously does not result in greater employment or earnings effects compared to the individual forms of advice on their own. This indicates that different forms of advice can potentially offset each others' effects, a consideration that policymakers should take into account when determining how to effectively combine potentially valuable policy tools.

One of the key findings of our analysis is that the positive direct effects of online job search advice can be partially or fully offset by negative indirect effects. As a growing number of unemployed workers receive similar advice, this provokes spillovers on other job seekers with whom they compete in the labor market. While there is little evidence that job seekers in the control group are affected, we found substantial negative indirect effects on other treated workers. These negative spillovers can be attributed to job seekers who, upon receiving advice, modify their job search strategies in a manner that ultimately intensifies competition and causes congestion within the newly targeted occupations.

The presence of strong spillover effects are of high relevance for researchers and policymakers 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 (Al-Ubaydli *et al.*, 2017, 2019; Muralidharan and Niehaus, 2017). On the other hand, our findings 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.

References

Abebe, G., A. S. Caria, M. Fafchamps, P. Falco, S. Franklin, and S. Quinn (2021): "Anonymity or distance? Job search and labour market exclusion in a growing African city," *The Review of Economic Studies*, 88, 1279–1310.

Al-Ubaydli, O., J. A. List, D. LoRe, and D. Suskind (2017): "Scaling for economists: Lessons from the non-adherence problem in the medical literature," *Journal of Economic Perspectives*, 31, 125–44.

Al-Ubaydli, O., J. A. List, and D. Suskind (2019): "The science of using science: Towards an understanding of the threats to scaling experiments," NBER Working Paper No. w25848.

Albrecht, J., B. Decreuse, and S. Vroman (2020): "Directed search with phantom vacancies," IZA Discussion Paper No. 13704.

Albrecht, J., G. J. Van den Berg, and S. Vroman (2009): "The aggregate labor market effects of the Swedish knowledge lift program," *Review of Economic Dynamics*, 12, 129–146.

Alfonsi, L., O. Bandiera, V. Bassi, R. Burgess, I. Rasul, M. Sulaiman, and A. Vitali (2020): "Tackling youth unemployment: Evidence from a labor market experiment in Uganda," *Econometrica*, 88, 2369–2414.

Altmann, S., S. Cairo, R. Mahlstedt, and A. Sebald (2022): "Do Job Seekers Understand the UI Benefit System (and Does It Matter)?" *IZA Discussion Paper No. 15747.*

Altmann, S., A. Falk, P. Heidhues, R. Jayaraman, and M. Teirlinck (2019): "Defaults and Donations: Evidence from a Field Experiment," *The Review of Economics and Statistics*, 101, 808–826.

Altmann, S., A. Falk, S. Jaeger, and F. Zimmermann (2018): "Learning about Job Search: A Field Experiment with Job Seekers in Germany," *Journal of Public Economics*, 164, 33–49.

Angelucci, M. and G. De Giorgi (2009): "Indirect effects of an aid program: how do cash transfers affect ineligibles' consumption?" *American Economic Review*, 99, 486–508.

Baird, S., J. A. Bohren, C. McIntosh, and B. Özler (2018): "Optimal design of experiments in the presence of interference," *Review of Economics and Statistics*, 100, 844–860.

Behaghel, L., B. Crépon, and M. Gurgand (2014): "Private and public provision of counseling to job seekers: Evidence from a large controlled experiment," *American Economic Journal: Applied Economics*, 6, 142–74.

Behaghel, L., S. Dromundo Mokrani, M. Gurgand, Y. Hazard, and T. Zuber (2022): "Encouraging and Directing Job Search: Direct and Spillover Effects in a Large Scale Experiment," *Banque de France, Working Paper No. 900.*

Belot, M., B. de Koning, D. Fourage, P. Kircher, P. Muller, and S. Phlippen (2023): "Stimulating occupational mobility among unemployed job seekers," *mimeo.*

Belot, M., P. Kircher, and P. Muller (2019): "Providing advice to jobseekers at low cost: An experimental study on online advice," *Review of Economic Studies*, 86, 1411–1447.

——— (2022): "Do the long-term unemployed benefit from automated occupational advice during online job search?" IZA Discussion Paper No. 15452.

Ben Dhia, A., B. Crépon, E. Mbih, L. Paul-Delvaux, B. Picard, and V. Pons (2022): "Can a Website Bring Unemployment Down? Experimental Evidence from France," NBER Working Paper No. 29914.

Benghalem, H., P. Cahuc, and P. Villedieu (2021): "The Lock-in Effects of Part-Time Unemployment Benefits," IZA Discussion Papers No. 14189.

Bhole, M., A. Fradkin, J. Horton, *et al.* (2021): "Information About Vacancy Competition Redirects Job Search," *mimeo.*

Bied, G., P. Caillou, B. Crépon, C. Gaillac, E. Pérennes, and M. Sebag (2023): "Designing labor market recommender systems: the importance of job seeker preferences and competition," *mimeo.*

Biewen, M., B. Fitzenberger, A. Osikominu, and M. Paul (2014): "The effectiveness of public-sponsored training revisited: The importance of data and methodological choices," *Journal of Labor Economics*, 32, 837–897.

Blundell, R., M. C. Dias, C. Meghir, and J. Van Reenen (2004): "Evaluating the employment impact of a mandatory job search program," *Journal of the European Economic Association*, 2, 569–606.

Cai, J. and A. Szeidl (2022): "Indirect Effects of Access to Finance," *mimeo.*

Card, D., J. Kluve, and A. Weber (2010): "Active labour market policy evaluations: A meta-analysis," *The Economic Journal*, 120, F452–F477.

——— (2017): "What works? A meta analysis of recent active labor market program evaluations," *Journal of the European Economic Association*, 16, 894–931.

Caria, S., S. Franklin, and M. Witte (2022): "Searching With Friends," *Journal of Labor Economics, forthcoming.*

Chetty, R. and E. Saez (2013): "Teaching the tax code: Earnings responses to an experiment with EITC recipients," *American Economic Journal: Applied Economics*, 5, 1–31.

Cheung, M., J. Egebark, A. Forslund, L. Laun, M. Rodin, and J. Vikström (2019): "Does job search assistance reduce unemployment? Experimental evidence on displacement effects and mechanisms," IFAU Working Paper 2019:25.

Crépon, B., E. Duflo, M. Gurgand, R. Rathelot, and P. Zamora (2013): "Do labor market policies have displacement effects? Evidence from a clustered randomized experiment," *The Quarterly Journal of Economics*, 128, 531–580.

Crépon, B., M. Ferracci, G. Jolivet, and G. J. van den Berg (2018): "Information shocks and the empirical evaluation of training programs during unemployment spells," *Journal of Applied Econometrics*, 33, 594–616.

Duflo, E. and E. Saez (2003): "The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment," *The Quarterly Journal of Economics*, 118, 815–842.

Egger, D., J. Haushofer, E. Miguel, P. Niehaus, and M. Walker (2022): "General Equilibrium Effects of Unconditional Cash Transfers: Experimental Evidence from Kenya," *forthcoming in Econometrica*.

Ferracci, M., G. Jolivet, and G. J. van den Berg (2014): "Evidence of treatment spillovers within markets," *Review of Economics and Statistics*, 96, 812–823.

Fluchtmann, J., A. M. Glenny, N. Harmon, and J. Maibom (2023): "Unemployed Job Search Across People and Over Time: Evidence from Applied-For Jobs," *forthcoming: Journal of Labor Economics*.

Gautier, P., P. Muller, B. van der Klaauw, M. Rosholm, and M. Svarer (2018): "Estimating equilibrium effects of job search assistance," *Journal of Labor Economics*, 36, 1073–1125.

Gee, L. K. (2019): "The more you know: information effects on job application rates in a large field experiment," *Management Science*, 65, 2077–2094.

Gibbons, R., L. F. Katz, T. Lemieux, and D. Parent (2005): "Comparative advantage, learning, and sectoral wage determination," *Journal of Labor Economics*, 23, 681–724.

Gibbons, R. and M. Waldman (1999): "A theory of wage and promotion dynamics inside firms," *The Quarterly Journal of Economics*, 114, 1321–1358.

Goldfarb, A. and C. Tucker (2019): "Digital economics," *Journal of Economic Literature*, 57, 3–43.

Groes, F., P. Kircher, and I. Manovskii (2015): "The U-shapes of occupational mobility," *The Review of Economic Studies*, 82, 659–692.

Herz, B. and T. Van Rens (2020): "Accounting for mismatch unemployment," *Journal of the European Economic Association*, 18, 1619–1654.

Horton, J. J. (2017): "The effects of algorithmic labor market recommendations: Evidence from a field experiment," *Journal of Labor Economics*, 35, 345–385.

Jäger, S., C. Roth, N. Roussille, and B. Schofer (2021): "Worker Beliefs About Outside Options," *IZA Discussion Paper No. 14963*.

Kircher, P. (2022): "Job search in the 21st Century," *Journal of the European Economic Association*, 20, 2317–2352.

Kudlyak, M., D. Lkhagvasuren, and R. Sysuyev (2013): "Systematic job search: New evidence from individual job application data," *FRB Richmond Working Paper No. 12-03R*.

Lalive, R., C. Landais, and J. Zweimüller (2015): "Market externalities of large unemployment insurance extension programs," *The American Economic Review*, 3564–3596.

Le Barbanchon, T., L. Hensvik, and R. Rathelot (2023): "How can AI improve search and matching? Evidence from 59 million personalized job recommendations," Working Paper.

Lise, J., S. Seitz, and J. A. Smith (2004): "Equilibrium policy experiments and the evaluation of social programs," NBER Working Paper No. 10283.

Michaillat, P. (2012): "Do matching frictions explain unemployment? Not in bad times," *American Economic Review*, 102, 1721–50.

Moscarini, G. and K. Thomsson (2007): "Occupational and Job Mobility in the US," *Scandinavian Journal of Economics*, 109, 807–836.

Moscarini, G. and F. G. Vella (2008): "Occupational mobility and the business cycle," NBER Working Paper No. 13819, National Bureau of Economic Research.

Mueller, A. I. and J. Spinnewijn (2022): "Expectations Data, Labor Market and Job Search," *Handbook of Economic Expectations*.

Mueller, A. I., J. Spinnewijn, and G. Topa (2021): "Job Seekers' Perceptions and Employment Prospects: Heterogeneity, Duration Dependence, and Bias," *American Economic Review*, 111, 324–63.

Muralidharan, K. and P. Niehaus (2017): "Experimentation at scale," *Journal of Economic Perspectives*, 31, 103–24.

Muralidharan, K., P. Niehaus, and S. Sukhtankar (2022): "General equilibrium effects of (improving) public employment programs," NBER Working Paper No. 23838.

Neal, D. (1999): "The complexity of job mobility among young men," *Journal of Labor Economics*, 17, 237–261.

Papageorgiou, T. (2014): "Learning your comparative advantages," *Review of Economic Studies*, 81, 1263–1295.

Patterson, C., A. Şahin, G. Topa, and G. L. Violante (2016): "Working hard in the wrong place: A mismatch-based explanation to the UK productivity puzzle," *European Economic Review*, 84, 42–56.

Pissarides, C. A. (2000): *Equilibrium unemployment theory*, MIT press.

Şahin, A., J. Song, G. Topa, and G. L. Violante (2014): "Mismatch unemployment," *American Economic Review*, 104, 3529–64.

Schiprowski, A. (2020): "The role of caseworkers in unemployment insurance: Evidence from unplanned absences," *Journal of Labor Economics*, 38, 1189–1225.

Skandalis, D. (2018): "Breaking News: Information About Firms' Hiring Needs Affects the Direction of Job Search," Tech. rep., mimeo.

Spinnewijn, J. (2015): "Unemployed but optimistic: Optimal insurance design with biased beliefs," *Journal of the European Economic Association*, 13, 130–167.

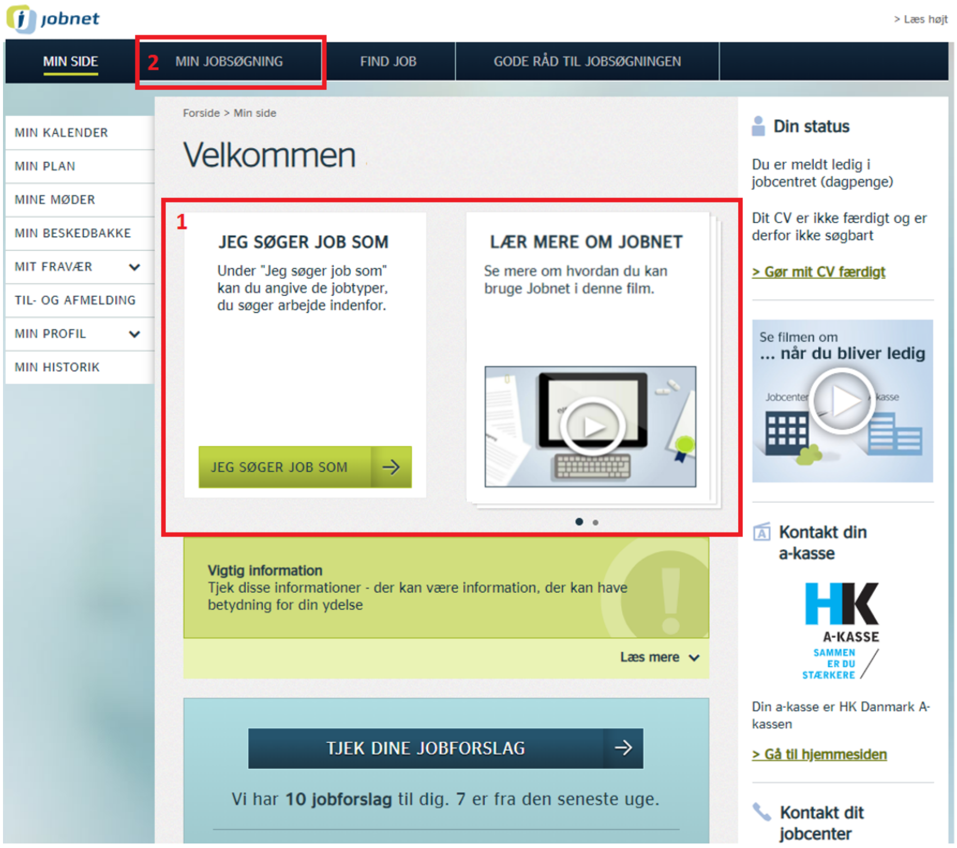
van der Klaauw, B. and H. Vethaak (2022): "Empirical Evaluation of Broader Job Search Requirements for Unemployed Workers," Tinbergen Institute Discussion Paper 2022-083/V.

Vazquez-Bare, G. (2022): "Identification and estimation of spillover effects in randomized experiments," *Journal of Econometrics*.

A Appendix

A.1 Illustration of study design

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

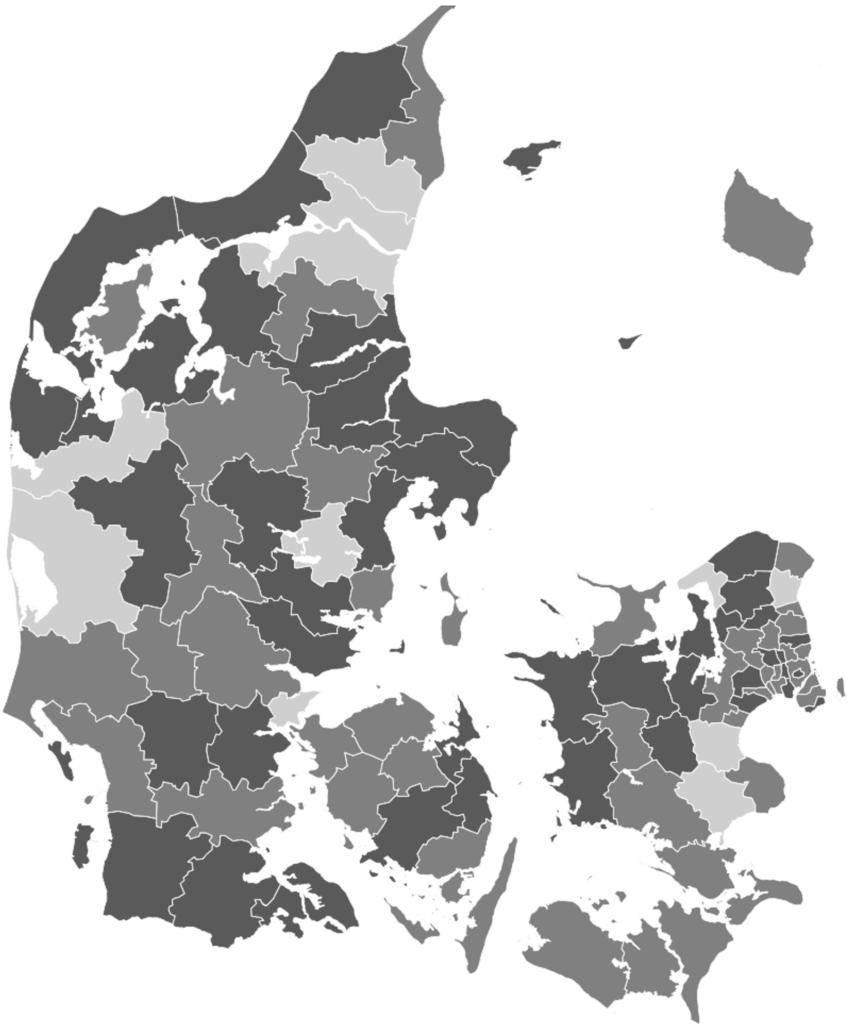
(B) Occupational information

(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)

A.2 Alternative definitions of local labor markets

Table A.4 shows direct and indirect treatment effects for six different alternative definitions of local labor markets and intensity measures:

(i) Baseline intensity measure: We analyze the commuting patterns of all Danish workers among the 98 municipalities in the three years preceding our experiment. Based on the resulting commuting matrix, we calculate the local treatment intensity for each municipality by considering the share of treated individuals (based on the three assignment regimes) in all other municipalities, weighted by the corresponding proportion of commuters between any pair of municipalities.

(ii) Alternative intensity 1: We calculate the share of treated individuals within a job seeker's own municipality and all bordering municipalities.

(iii) Alternative intensity 2: We calculate the share share treated individuals within a job seeker's own municipality and all neighboring municipalities within all occupations stored in job seekers' search profile (measured at the 3-digit ISCO level)

(iv) Alternative intensity 3: We calculate the share of treated individuals within each of the 11 Danish provinces (NUTS3 regions).

(v) Alternative intensity 4: We calculate the share of treated individuals within the three most popular destination municipalities based on the commuting patterns of all Danish workers among the 98 municipalities in the three years preceding our experiment.

(vi) Alternative intensity 5: We calculate the share of treated individuals who actually applied to comparable vacancies in the past. Therefore, we consider all registered job applications of individuals in the experimental sample during the last two years before the start of the intervention and calculate the share of treated that applied to any given combination of zip codes (2-digits) and occupations (3-digits). Afterwards, we calculate the weighted average of treatment intensities over an individual's application portfolio.

A.3 Additional Tables

Table A.1: Determinants of local treatment intensity

		Treatment status			
	Full sample (1)	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	0.0016	0.0018	0.0001	-0.0002	-0.0024
	(0.0017)	(0.0025)	(0.0023)	(0.0020)	(0.0023)
36 - 45 years	-0.0013	0.0009	-0.0026	-0.0032	-0.0064*
	(0.0023)	(0.0026)	(0.0035)	(0.0028)	(0.0034)
46 - 55 years	0.0001	0.0010	-0.0016	0.0007	-0.0043
	(0.0028)	(0.0027)	(0.0049)	(0.0033)	(0.0036)
56 - 65 years	-0.0007	-0.0005	-0.0014	-0.0006	-0.0045
	(0.0031)	(0.0031)	(0.0048)	(0.0040)	(0.0036)
Married	-0.0001	-0.0031*	0.0021	0.0011	0.0004
	(0.0015)	(0.0017)	(0.0019)	(0.0021)	(0.0021)
Male	0.0005	0.0005	0.0018	-0.0002	0.0025
	(0.0011)	(0.0012)	(0.0014)	(0.0018)	(0.0018)
Any children	-0.0006	0.0018	-0.0021	-0.0024	-0.0016
	(0.0017)	(0.0020)	(0.0017)	(0.0021)	(0.0017)
Danish	-0.0058	-0.0145**	0.0025	0.0022	0.0017
	(0.0049)	(0.0062)	(0.0040)	(0.0035)	(0.0036)
Level of education (ref. no secondary or missing)					
Lower secondary	0.0038	0.0097*	-0.0019	-0.0043	0.0024
	(0.0038)	(0.0050)	(0.0045)	(0.0043)	(0.0035)
Upper secondary	0.0024	0.0060	-0.0020	-0.0009	0.0006
	(0.0028)	(0.0039)	(0.0036)	(0.0036)	(0.0032)
BA or equivalent	0.0044*	0.0062*	0.0010	-0.0002	0.0026
	(0.0025)	(0.0033)	(0.0029)	(0.0027)	(0.0024)
MA or equivalent	0.0067*	0.0046	0.0040	0.0026	0.0064*
	(0.0040)	(0.0036)	(0.0048)	(0.0041)	(0.0036)
Elapsed unemployment duration (ref. less than one month)					
1 - 3 months	-0.0006	-0.0025	0.0020	0.0014	-0.0011
	(0.0012)	(0.0015)	(0.0022)	(0.0018)	(0.0020)
4 - 6 months	-0.0022	-0.0036**	-0.0001	0.0008	-0.0014
	(0.0016)	(0.0015)	(0.0027)	(0.0022)	(0.0019)
7 - 12 months	-0.0003	-0.0019	0.0048*	0.0030*	-0.0009
	(0.0016)	(0.0019)	(0.0025)	(0.0018)	(0.0020)
13 - 24 months	-0.0012	-0.0042*	0.0060*	0.0022	-0.0000
	(0.0020)	(0.0021)	(0.0033)	(0.0022)	(0.0027)
more than 24 months	-0.0007	0.0024	-0.0019	0.0018	0.0004
	(0.0034)	(0.0036)	(0.0063)	(0.0047)	(0.0050)

Continued on next page.

Continued from previous page.

Labor earnings in year $t-x$ (in 100,000DKK)					
t - 1	0.0040	-0.0068	0.0035	0.0070	0.0088**
	(0.0045)	(0.0059)	(0.0053)	(0.0048)	(0.0040)
t - 2	-0.0010	-0.0065	-0.0021	-0.0001	0.0006
	(0.0023)	(0.0093)	(0.0031)	(0.0020)	(0.0042)
t - 3	-0.0013	-0.0020	0.0105	-0.0039	-0.0096
	(0.0053)	(0.0043)	(0.0069)	(0.0054)	(0.0075)
Average weekly working hours (×100) in year $t-x$					
t - 1	-0.0093	0.0008	-0.0016	-0.0138*	-0.0107
	(0.0067)	(0.0068)	(0.0081)	(0.0076)	(0.0077)
t - 2	0.0032	0.0118	-0.0007	0.0003	-0.0074
	(0.0043)	(0.0097)	(0.0056)	(0.0051)	(0.0067)
t - 3	-0.0106	-0.0032	-0.0211***	-0.0101	-0.0042
	(0.0074)	(0.0065)	(0.0070)	(0.0083)	(0.0114)
Previous occupation (ref. none)					
Managerial position	0.0024	0.0031	-0.0059	0.0062	0.0003
	(0.0026)	(0.0044)	(0.0043)	(0.0049)	(0.0034)
Professional position	0.0043**	0.0069***	-0.0031	0.0009	0.0054**
	(0.0020)	(0.0024)	(0.0028)	(0.0024)	(0.0027)
Technicians and associated position	0.0067**	0.0077**	-0.0010	0.0050**	0.0040
	(0.0030)	(0.0031)	(0.0031)	(0.0025)	(0.0038)
Clerical support worker	0.0059*	0.0105***	-0.0010	0.0027	0.0046
	(0.0031)	(0.0035)	(0.0034)	(0.0031)	(0.0032)
Service sales worker	0.0027	0.0040**	0.0002	0.0015	0.0026
	(0.0018)	(0.0018)	(0.0019)	(0.0024)	(0.0026)
Agricultural worker	0.0041	0.0074	-0.0020	0.0023	0.0094
	(0.0048)	(0.0066)	(0.0110)	(0.0073)	(0.0087)
Craft worker	-0.0003	0.0034	-0.0072**	-0.0003	0.0008
	(0.0021)	(0.0028)	(0.0034)	(0.0036)	(0.0034)
Plant machine operator	0.0036	0.0042	-0.0021	0.0048	0.0069
	(0.0061)	(0.0057)	(0.0060)	(0.0072)	(0.0076)
Elementary occupation	0.0030	0.0054***	-0.0037	0.0023	0.0039
	(0.0018)	(0.0021)	(0.0024)	(0.0024)	(0.0028)
Labor market tightness	0.0066*	0.0077**	0.0023	-0.0003	0.0019
	(0.0035)	(0.0034)	(0.0026)	(0.0033)	(0.0025)
Constant	0.4908***	0.6019***	0.6302***	0.6312***	0.6295***
	(0.0839)	(0.0893)	(0.0166)	(0.0159)	(0.0165)
No. of observations	92,098	31,966	19,990	20,225	19,917
Mean value dep. variable	0.644	0.592	0.673	0.672	0.672
P-value joint significance	0.546	0.663	0.453	0.140	0.435

Note: Depicted are regression coefficients where the dependent variable refers to the continuous measure of the local treatment intensity. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level.

Table A.2: 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.)[(b)]	-0.015	-53.0	-8,533			
	(0.022)	(46.5)	(10,379)			
Local treatment intensity (ref. low intensity)[(c)]						
Medium intensity				-0.006	-19.5	-2,554
				(0.009)	(21.3)	(4782)
High intensity				-0.005	-22.7	-4,340
				(0.012)	(22.8)	(4,876)
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	774	146,960
P-value joint sign. treatment intensity				0.792	0.597	0.519

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.
[(a)] Measured in DKK.
[(b)] Continuous treatment intensity as depicted in Figure 1.
[(c)] Categorical variable with indicators for low (bottom tercile), medium (middle tercile) and high (top tercile) treatment intensities.

Table A.3: Sensitivity analysis: accounting for other dimensions of heterogeneity

Dependent variable	Outcomes measured within 12 months after start of intervention					
	Working hours	Labor earnings$^{(a)}$ (in DKK)	Working hours	Labor earnings$^{(a)}$ (in DKK)	Working hours	Labor earnings$^{(a)}$ (in DKK)
	(1)	(2)	(3)	(4)	(5)	(6)
Recommendation treatment	72.1**	18,222**	83.8**	17,487*	86.1**	18,046**
	(35.0)	(8,264)	(40.6)	(9,199)	(38.5)	(9,061)
Vacancy treatment	93.2**	19,577**	76.6*	17,147*	76.4*	17,281*
	(37.5)	(8,301)	(44.6)	(9,470)	(41.9)	(9,423)
Joint treatment	46.0	11,427	40.6	12,068	40.2	12,161
	(43.3)	(8,551)	(48.4)	(9,278)	(46.7)	(9,269)
Local treatment intensity (cont.)	-19.8	1,783	-26.2	865	-92.0	-18,045
	(23.2)	(4,619)	(23.2)	(4,488)	(167.7)	(22,629)
× Recommendation treatment	-100.5*	-25,346**	-101.8*	-25,422**	-97.9*	-24,079*
	(52.2)	(12,301)	(54.0)	(12,718)	(53.7)	(12,572)
× Vacancy treatment	-112.5**	-25,112**	-111.6*	-25,066**	-104.7*	-23,244*
	(55.4)	(12,388)	(56.4)	(12,534)	(55.6)	(12,681)
× Joint treatment	-61.5	-15,946	-50.5	-14,864	-44.3	-13,212
	(64.7)	(12,715)	(67.3)	(12,887)	(69.3)	(13,281)
No. of observations	92,098	92,098	92,098	92,098	92,098	92,098
Mean value dep. variable	779	146,214	779	146,214	779	146,214
Controls for individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
interacted with treatment status	No	No	Yes	Yes	Yes	Yes
interacted with treatment intensity	No	No	No	No	Yes	Yes

Note: The table reports the results of regression where we interact treatment indicators and local treatment intensities as described by Equation 5 when accounting for other dimensions of heterogeneity. In specification (3) and (4), we control for interaction effects of the treatment status and individual-characteristics (as depicted in Table 3). Additionally, in specifications (5) and (6), we control for interaction effects of local treatment intensities and individual-characteristics. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level.

Table A.4: Sensitivity analysis: alternative definitions of local labor markets and intensity measures

Dependent variable	A. Working hours within 12 months after start of intervention					
Treatment intensity	Baseline intensity measure	Alternative 1 neighboring municipalities	Alternative 2 municipality-occupation	Alternative 3 provinces (11 regions)	Alternative 4 commuting zone: top-3	Alternative 5 application portfolio
	(1)	(2)	(3)	(4)	(5)	(6)
Recommendation treatment	72.1**	54.7*	41.9	86.5**	65.4***	123.9***
	(35.0)	(28.8)	(28.1)	(37.1)	(19.5)	(46.2)
Vacancy treatment	93.2**	80.0**	77.1**	63.4*	64.3***	48.7
	(37.5)	(32.1)	(32.0)	(34.6)	(19.5)	(48.8)
Joint treatment	46.0	26.4	23.4	30.7	40.5**	35.1
	(43.3)	(33.6)	(34.7)	(37.6)	(18.6)	(55.3)
Local treatment intensity	-19.8	3.0	7.2	-37.4	-37.2*	-39.5
	(23.2)	(24.5)	(21.3)	(39.7)	(20.6)	(32.0)
× Recommendation treatment	-100.5*	-76.8*	-58.2	-120.3**	-92.9***	-174.1**
	(52.2)	(42.1)	(40.2)	(56.5)	(31.6)	(71.3)
× Vacancy treatment	-112.5**	-94.7**	-90.6*	-66.9	-70.8**	-43.9
	(55.4)	(46.6)	(46.1)	(52.8)	(31.1)	(73.2)
× Joint treatment	-61.5	-34.7	-30.8	-37.7	-53.7*	-42.9
	(64.7)	(49.7)	(50.2)	(55.2)	(29.9)	(82.9)
No. of observations	92,098	92,098	92,098	92,098	92,098	90,210
Mean value outcome	779	779	779	779	779	777

Dependent variable	B. Labor earnings in DKK within 12 months after start of intervention					
Treatment intensity	Baseline intensity measure	Alternative 1 neighboring municipalities	Alternative 2 municipality-occupation	Alternative 3 provinces (11 regions)	Alternative 4 commuting zone: top-3	Alternative 5 application portfolio
	(7)	(8)	(9)	(10)	(11)	(12)
Recommendation treatment	18,222**	13,740**	9,576	22,255***	17,013***	35,017***
	(8,264)	(6,567)	(6,392)	(7,774)	(4,528)	(11,755)
Vacancy treatment	19,577**	16,480**	15,991**	11,633	12,832***	16,693
	(8,301)	(6,749)	(6,877)	(7,753)	(4,874)	(10,811)
Joint treatment	11,426	7,901	6,600	5,460	8,857**	18,722
	(8,551)	(6,653)	(6,815)	(7,502)	(3,816)	(11,334)
Local treatment intensity (cont.)	1,783	3,833	5,035	-3,194	-3,887	2,690
	(4,619)	(3,916)	(3,490)	(6,819)	(4,113)	(5,461)
× Recommendation treatment	-25,346**	-18,840*	-12,884	-30,709***	-24,068***	-49,830***
	(12,301)	(9,595)	(9,305)	(11,475)	(7,145)	(17,770)
× Vacancy treatment	-25,112**	-20,661**	-20,061**	-12,776	-15,183**	-20,628
	(12,388)	(9,914)	(10,060)	(11,726)	(7,560)	(16,138)
× Joint treatment	-15,946	-10,945	-9,233	-6,570	-12,076**	-26,690
	(12,715)	(9,750)	(9,899)	(10,950)	(5,894)	(17,006)
No. of observations	92,098	92,098	92,098	92,098	92,098	90,210
Mean value dep. variable	146,214	146,214	146,214	146,214	146,214	145,542

Note: The table reports the results of interacted regression of treatment indicators and local treatment intensities for various definitions of local labor market and intensity measures. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level.

Table A.5: Aggregate effects of job search advice

Dependent variable	Differences in average outcomes within municipality over 12 months	
	Log working hours	Log labor earnings
	(1)	(2)
Local treatment intensity	0.323	0.604***
	(0.200)	(0.225)
Local treatment intensity squared	-0.302	-0.527**
	(0.187)	(0.206)
P-value joint significance	0.274	0.018
No. of observation (municipalities)	98	98
Mean value dep. variable	0.009	-0.008

Note: The table reports the results of a quadratic regressions at the municipal-level. The dependent refers to the average working hours, respectively labor earnings accumulated over a period of 12 months aggregated at the municipality level. For both variables, we consider the log difference between the experimental sample and the placebo sample (i.e. the stock of UI benefit recipients one year before the start of the intervention). We use sample weights reflecting the number of unemployed workers in each municipality as observed in the experimental sample. */**/*** indicates statistical significance at the 10%/5%/1%-level.