The Direct and Indirect Effects of Online Job Search Advice*

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Abstract

We study how online job search advice affects job search behavior and labor market outcomes of unemployed workers. In a large-scale field experiment embedded in the online platform of the Danish public employment service, we provide job seekers with vacancy information and occupational recommendations. Using a two-stage randomized design with regionally varying treatment intensities, we examine both direct effects of advice and treatment spillovers. We find that advice significantly increases employment and earnings when provided to a limited share of job seekers. As treatment intensity rises, these effects diminish and eventually disappear. The decline is driven by negative spillovers among treated job seekers, consistent with increased congestion in the occupations toward which job seekers redirect their search. Spillover effects on untreated job seekers are heterogeneous and depend on how advice alters occupation-specific competition in local labor markets.

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

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

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1 Introduction

Information frictions are a pervasive feature of the job search process. Workers often lack information about potential job matches (Jäger *et al.*, 2024; Belot *et al.*, 2019) or their overall employment prospects (Mueller *et al.*, 2021; Mueller and Spinnewijn, 2023; Spinnewijn, 2015). To address these challenges and assist job seekers, labor market policy has long relied on job search assistance and counseling. Traditionally, this role has been fulfilled by caseworkers, coaches, and counselors. In recent years, however, both public employment services and private providers have increasingly turned to digital tools for job search assistance (see Kircher, 2022, for an overview).

As in other economic settings, digital advice offers two potential advantages in the context of job search. First, it allows policymakers to disseminate information at low marginal costs, potentially reducing search costs and information frictions at scale. Second, it enables the tailoring of advice to individual job seekers, which may increase the relevance and usefulness of the information provided. While these benefits are straightforward in settings with non-rival goods (see, e.g., Goldfarb and Tucker, 2019), the competitive nature of labor markets implies that advice may generate spillover effects on other market participants (see Crépon *et al.*, 2013; Gautier *et al.*, 2018). These indirect effects must be weighed against the direct benefits experienced by individuals who receive the advice.

In this paper, we study the direct and indirect effects of online job search advice on labor market outcomes of unemployed workers. We report results from a large-scale randomized controlled trial among the universe of unemployment insurance (UI) recipients in Denmark (N$\sim$92,000). In the experiment, we exogenously vary the content of a new dashboard that provides personalized information to job seekers on the central online platform of the public employment service. We focus on two forms of advice commonly found on online job boards, which we compare to a control group receiving only generic information. First, we provide job seekers with information about the number of vacant positions in those occupations that they have stored in their personal job search profile. Second, job seekers receive referrals to suitable alternative occupations that may be a good fit based on their personal search profile.[1]

[1] Our treatments build on evidence of substantial occupational mismatch (Şahin *et al.*, 2014; Herz and Van Rens, 2020; Patterson *et al.*, 2016) and learning about occupation-specific prospects (see, e.g., Neal,

The two types of advice aim to reduce reduce frictions in the job search process by providing information about occupation-specific labor market conditions (via vacancy information) and the alignment of job seekers' skills with alternative occupations (via occupational recommendations), respectively. Using a job-search framework, we illustrate how such information can lead job seekers to update beliefs about these dimensions and, in turn, reallocate their search effort across occupations. While this reallocation may improve the labor market prospects of job seekers who receive advice, it can also generate spillover effects on other job seekers. As more individuals receive similar advice, competition may intensify in the occupations they move toward and ease in those they move away from.

To empirically investigate the direct and indirect effects of advice, we implement a two-stage randomized trial. In the first stage, we exogenously vary the share of job seekers receiving advice by assigning each municipality in Denmark to one of three treatment-intensity regimes. In the second stage, individual job seekers are assigned either to a control group or to one of three treatment arms, in which they receive vacancy information, occupational recommendations, or both.

In the first part of our analysis, we examine the direct and indirect effects of online job search advice, considering the different forms of advice jointly. We aggregate across the three treatment arms and compare labor market outcomes of treated and untreated job seekers across regions with higher and lower treatment intensity. We find that advice significantly improves labor market outcomes when the share of treated individuals is moderate. In regions with intermediate treatment intensity (where 60% of job seekers receive some form of advice), treated job seekers experience 2–3% higher employment and earnings over the first six months of the intervention relative to the control group. Over a 12-month horizon, we continue to observe positive effects on cumulative working hours and earnings, whereas differences in employment rates are no longer statistically significant. At the same time, we document substantial treatment spillovers among treated job seekers. In regions assigned to the high treatment-intensity regime (where 90% of job seekers receive advice), treated individuals exhibit significantly lower employment, working hours, and earnings than their counterparts in medium-intensity regions. These negative spillovers are robust to alternative definitions of local labor

1999; Gibbons and Waldman, 1999; Gibbons *et al.*, 2005; Groes *et al.*, 2015; Papageorgiou, 2014). They also draw on findings that a broader occupational focus increases job interviews (Belot *et al.*, 2019).

markets (e.g., accounting for inter-municipal commuting flows) and are sufficiently large to fully offset the positive direct effects of advice at high treatment intensity. By contrast, we find no evidence of average spillover effects on the labor market outcomes of job seekers in the control group.

Using data on registered job applications, we show that the positive labor market effects of advice in regions with medium treatment intensity are accompanied by a shift in search toward occupations with better job opportunities, as reflected in lower competition. However, as more job seekers receive advice, the effects on occupational competition reverse, eventually creating congestion in the newly targeted occupations. Consistent with this mechanism, we find that spillover effects on job seekers in the control group vary systematically depending on (1) how the intervention alters the competition they face from treated job seekers and (2) whether initial labor market tightness is distributed evenly or unevenly across occupations within a region.

The second part of our analysis examines the effects of different types of advice. Both occupational recommendations and vacancy information increase employment and earnings when the share of treated individuals is modest, but their effectiveness declines at higher treatment intensities. While both treatments improve labor market outcomes, they do so through distinct shifts in job seekers' search behavior. Job seekers who receive occupational referrals tend to follow the recommendations, as reflected in more applications to, and higher employment in, the recommended occupations. This pattern is consistent with the notion that recommendations increase the perceived attractiveness of searching in these occupations, for example, by conveying information about the match between job seekers' skills and occupational requirements.

By contrast, job seekers exposed to vacancy information, on average, concentrate their search more strongly on their "core" occupations—those stored in their search profile prior to the intervention—with most additional employment occurring in these occupations. This pattern suggests that, on average, job seekers interpret the obtained vacancy information as a positive signal regarding the returns to searching within their core occupations. At the same time, the resulting occupational shifts vary systematically with initial labor market conditions, consistent with job seekers using vacancy information as a signal of occupation-specific labor market tightness. In particular, for individuals who initially search in low-tightness occupations, vacancy information increases employment and earnings in non-core occupations.

Finally, our results suggest that the positive effects of vacancy information and occupational recommendations do not simply add up when combined. Treatment effects in the combined treatment, where job seekers receive both types of advice, are small and generally not statistically significant. This pattern is consistent with the idea that different forms of advice may partially offset each other, for instance, by providing conflicting signals about which occupations to target or by increasing the cognitive demands of processing multiple pieces of information simultaneously.

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 developed in a number of contemporaneous studies. Consistent with our results for occupational recommendations, these studies show that referrals to alternative occupations encourage job seekers to broaden their search, increasing the number of job interviews (Belot *et al.*, 2019) and stimulating employment among the long-term unemployed (Belot *et al.*, 2025b) and job seekers in structurally weak labor markets (Belot *et al.*, 2025a). These findings align with our results, which show that occupational recommendations are particularly effective for long-term unemployed workers and for job seekers initially searching in slack occupations. In contrast, Ben Dhia *et al.* (2022) find no employment effects from encouraging job seekers to use a private job-search assistance website.[2] Le Barbanchon *et al.* (2023) and Behaghel *et al.* (2024) study alternative recommender systems that direct job seekers toward specific job postings and toward firms likely to recruit, respectively, and find positive, quantitatively modest, employment effects.

Our paper provides the first direct evidence that occupation-specific job search advice can generate substantial spillover effects among both treated and untreated job seekers. While Le Barbanchon *et al.* (2023) and Behaghel *et al.* (2024) consider potential congestion effects arising from recommender systems, their analyses focus on congestion at the vacancy or firm level. By contrast, our design examines worker-level spillovers by inducing exogenous variation in the share of treated individuals across local labor markets, allowing us to assess how treatment intensity alters the effectiveness

[2] More distantly related, van der Klaauw and Vethaak (2022) show that mandatory requirements to search more broadly may even reduce job finding.

of advice for individual job seekers. We show that spillover effects can reduce or even fully offset the positive direct effects of advice for treated job seekers and reshape occupation-specific competition in ways that also affect job seekers who receive no advice.

Our results further contribute to the literature on information frictions in labor markets by showing that different types of advice—occupational recommendations and vacancy information—can improve unemployed workers' labor-market integration when provided at limited scale. These findings underscore the role of informational constraints and, more broadly, labor supply frictions as barriers to job seekers' reemployment, complementing related evidence from developing-country contexts (see, e.g., Abebe *et al.*, 2021; Alfonsi *et al.*, 2020; Caria *et al.*, 2023). The magnitude of our effects should be interpreted in light of the fact that the intervention was directly embedded in the official online platform of the Danish public employment service, which all UI recipients are required to use—an implementation that likely generates stronger responses than one-off interventions or encouragement designs. Taken together, our findings suggest that well-designed digital job search tools can meaningfully alleviate informational constraints among unemployed workers.

More broadly, our results highlight the importance of accounting for spillover effects when designing and evaluating policy interventions. Our paper thus contributes to a growing body of work documenting spillover effects across a wide range of economic settings, including labor market policies and public employment programs (Albrecht *et al.*, 2009; Lalive *et al.*, 2015; Lise *et al.*, 2004; Muralidharan *et al.*, 2023), cash transfers (Angelucci and De Giorgi, 2009; Egger *et al.*, 2022), retirement savings (Duflo and Saez, 2003), or firms' access to loans (Cai and Szeidl, 2024). Spillovers pose a fundamental challenge for personalized interventions, as individuals with similar characteristics tend to receive similar recommendations and adjust their behavior in correlated ways. Given the growing interest in algorithmic recommendations (see Horton, 2017; Kircher, 2022), our findings suggest that interventions that are effective at small scale may be difficult to roll out successfully to the full population (see Al-Ubaydli *et al.*, 2017, 2019; Muralidharan and Niehaus, 2017). At the same time, our results point to potential ways to mitigate such spillovers, including the design of recommender systems that explicitly account for equilibrium effects (see Naya *et al.*, 2023; Behaghel *et al.*, 2024), or further targeting advice toward groups that are most likely to benefit, such as the long-term unemployed or workers searching in slack labor markets.

Finally, our work contributes to the literature on traditional job search assistance programs (see, e.g., Card *et al.*, 2010, 2017, for overviews), counseling services (Behaghel *et al.*, 2014; Bennmarker *et al.*, 2013; Schiprowski, 2020) and information provision (Altmann *et al.*, 2018, 2022). By combining a large-scale field experiment with detailed administrative data on job applications and labor market outcomes, we shed light on mechanisms that are often difficult to study in the absence of rich data.[3] Related to the indirect effects we document, Crépon *et al.* (2013), Gautier *et al.* (2018), and Cheung *et al.* (2025) show that traditional job search assistance programs generate displacement effects that reduce the labor-market prospects of non-treated individuals. These spillovers are typically attributed to increases in the search productivity of treated job seekers. By contrast, the indirect effects in our study appear to be driven primarily by job seekers redirecting their search across occupations.

2 Study Design

To study the labor market effects of online job search advice, we conducted a randomized controlled trial using a digital dashboard on the official online platform of the public employment service in Denmark (*jobnet.dk*). In our experiment, we exogenously vary (1) the type of advice provided to individual job seekers and (2) the share of treated job seekers across regions.

2.1 The online platform and dashboard

The *jobnet.dk* platform serves as the primary interface between unemployed workers and the public employment services. For all UI benefit recipients in Denmark, it is mandatory to log in to the platform at least once a week. The platform incorporates a comprehensive vacancy database, which is one of the two most frequently used job boards in Denmark and includes approximately 90% of all posted job openings. Similar to public and private job boards studied in countries such as the UK (Belot *et al.*, 2025b), Sweden (Le Barbanchon *et al.*, 2023), and France (Behaghel *et al.*, 2024),

[3] A methodologically related study using job application data is Kuhn and Shen (2023), which examines the impact of explicit gender requests in job postings on job search behavior and labor market outcomes.

job seekers can explore the vacancy database either by using a free keyword search or by specifying search parameters in the job board's menu (e.g., preferred geographical location, occupation, or working time). Besides the job board, the platform offers various tools to support unemployed job seekers. In particular, unemployed workers use the platform to register and deregister for unemployment benefits, learn about their benefit entitlements, schedule meetings with their caseworker, upload their CVs, and document their job applications.

Our experiment makes use of a dashboard that was newly rolled out as part of the study. The dashboard is embedded in the upper central part of the platform's landing page and is visible to job seekers immediately upon login (see Appendix Figure A.1 for an illustration). In the experiment, we exogenously vary the information cards displayed to each job seeker on the dashboard. The dashboard also allows us to tailor the content of the information cards to each job seeker's personal situation. Specifically, the information cards underlying our treatments build on individuals' *personal job search profiles*, which all job seekers are required to complete when registering as unemployed. In the profile, job seekers store the occupations that they are interested in pursuing, choosing from approximately 1,020 options categorized using the Danish adaptation of the international occupation classification system (ISCO). Throughout the study, we define a job seeker's *core occupations* as those stored in their personal job search profile at the start of the intervention, distinguishing them from all other occupations, which we refer to as *non-core occupations*. Using the core occupations of each job seeker as a foundation, the experiment provides individuals with two types of online job search advice, delivered through different information cards.[4]

Occupational recommendations: The *recommendation card* provides job seekers with recommendations for related alternative occupations based on the ones they have stored in their search profile (see Panel A of Appendix Figure A.2). Each 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. Like Belot *et al.* (2019), we generated these

[4]Independent of our experiment and identical across all treatment arms, the platform provides job seekers with a list of ten suggested vacancies based on their core occupations. The list is located below the dashboard and job seekers are expected to review the suggestions on a weekly basis.

recommendations from data about successful recent labor market transitions. For each occupation, we counted the number of transitions to other occupations and created a list with the five most popular alternatives.[5] The information card displays a maximum of three out of these five alternative occupations, provided they are not already included in the job seeker's search profile. These *recommended occupations* are thus a subset of the job seeker's non-core occupations, selected based on anticipated skill alignment. Job seekers can view current vacancies in these occupations by clicking on the corresponding recommendation. Moreover, the information card includes a link to the job search profile page, where job seekers can review and, if desired, modify their personal profiles.

Vacancy information: The *vacancy information card* informs job seekers about the current total of available vacancies for their core occupations (see Panel B of Appendix Figure A.2). 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 platform. Like the recommendation card, the vacancy card includes a link to the individual's personal search profile, where job seekers can also access a list of all vacancies in their core occupations.

The idea of the vacancy card is to provide job seekers with information about local labor demand in their core occupations. While labor market tightness may, in principle, be an even more informative measure (see also Section 3), implementing such a metric would have required substantial reprogramming of the platform and was therefore not technically feasible. In addition, many job seekers may not be familiar with tightness measures, whereas vacancy counts are more tangible and intuitive. Reassuringly, vacancy counts and labor market tightness are strongly correlated in our data ($\rho = 0.52$).

Generic information: In addition to the two cards containing personalized information, the dashboard also includes two *generic cards*. The first provides job seekers with a link to their personal search profile—just like the recommendation and vacancy

[5]We examine register data covering all unemployment-to-job transitions in Denmark from 2013 to 2016. We augment these data with information on current vacancies for each occupation and a measure of educational overlap across occupations. This ensures that our recommendations exclude occupations without available vacancies or those requiring education beyond the job seeker's qualifications. To further assess the informativeness of past transitions and the stability of occupation-specific labor market conditions, we compute annual vacancy counts by occupation and municipality from 2013–2019. Pairwise year-to-year correlations range from 0.90 to 0.97, indicating highly stable relative demand across occupations.

cards—but it does not display any additional personalized information (see Panel C of Appendix Figure A.2). The other generic card (see Panel D of Figure A.2) provides a link to a video offering general information about the features and functionalities of the online platform. As detailed in Section 2.2, the generic cards are included to keep the dashboard structure identical across treatment arms (e.g., always displaying the same number of cards to avoid salience- or Hawthorne-type effects).

2.2 Randomized controlled trial

To investigate the direct and indirect effects of search advice, we implemented a two-stage randomized design in which treatment assignment was randomized at both the individual and regional levels (see also Crépon *et al.*, 2013; Baird *et al.*, 2018).

At the *individual level*, we exogenously vary the information cards shown to job seekers. Each job seeker's dashboard includes two of four information cards, determined by their assigned treatment status (see Table 1 for an overview). For individuals assigned to the control group, the dashboard displays the two generic cards. Furthermore, we randomly assigned job seekers to three treatment arms to study the effects of occupational recommendations, vacancy information, and their combination. Job seekers in the *recommendation treatment* encounter the recommendation card along with the generic video card. Job seekers assigned to the *vacancy treatment* see the vacancy card and the video card. Finally, individuals in the *combined treatment* are exposed to both the vacancy and recommendation cards.

Table 1: Information cards displayed for different treatment arms

	Treatment arm	**First card**	**Second card**
	(1) Control group	Generic: search profile (C)	Generic: video (D)
Any advice	(2) Recommendation treatment	Recommendation card (A)	Generic: video (D)
Any advice	(3) Vacancy treatment	Vacancy card (B)	Generic: video (D)
Any advice	(4) Combined treatment	Recommendation card (A)	Vacancy card (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.

Identifying the causal effects of different types of advice requires that the four treatment arms differ only in whether job seekers receive occupational recommendations, vacancy information, both, or neither. To satisfy this requirement, the generic search profile card—presented to the control group in place of personalized advice—closely mirrors the structure of the vacancy and recommendation cards by also providing a shortcut to the job seeker's personal search profile. This rules out potential concerns that treatment differences reflect this shortcut rather than the advice itself. All treatment arms also display the same number of cards to avoid differences in salience or interface complexity. As a second card, job seekers in the recommendation treatment, vacancy treatment, and control group are all exposed to the same generic video card. The only exception is the combined treatment, in which the generic video card is not displayed on the dashboard. Job seekers in this group can, however, readily access the video via a dedicated subpage on the platform, reachable with just one click.

At the *regional level*, we randomly allocated each of the 98 Danish municipalities into one of three distinct regimes: super-control, medium-intensity, and high-intensity. To ensure that regions with different assignment probabilities exhibited similar characteristics, this stage builds on a stratified randomized design. 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 treatment-intensity regimes.

In the second stage of randomization, we allocated each job seeker to a treatment arm based on the pre-assigned treatment intensity of their municipality of residence. In ten municipalities, all unemployed workers were assigned exclusively to the control group—the so-called *super-control group*. In all other municipalities, unemployed workers were randomly assigned to either the control group or one of the three treatment arms (recommendation treatment, vacancy treatment, or combined treatment). In 44 municipalities—the *medium-intensity regime*—job seekers faced a 40% probability of being assigned to the control group and a 60% probability of being assigned to treatment, equally distributed across treatment arms (i.e., a 20% probability for each treatment arm). In the remaining 44 municipalities—the *high-intensity regime*—job seekers faced a 10% probability of being assigned to the control group and a 90% probability of being assigned to treatment (30% per treatment arm). This procedure, summarized in Table 2 and Appendix Figure A.3, ensures random assignment of individuals to the four treatment groups within each municipality.

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

Assignment regime	No. of municipalities	Treatment weights: Control group	Recom. treatment	Vacancy treatment	Combined treatment	No. of individuals
Super-control	10	100%	0%	0%	0%	10,100
Medium-intensity	44	40%	20%	20%	20%	45,232
High-intensity	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 treatment intensity regimes, while columns 3–6 depict the share of job seekers assigned to each of the four treatment arms.

Table 1 and Table 2 illustrate how our experimental design allows us to study the direct and indirect effects of online job search advice. First, comparing outcomes for job seekers who receive no advice (group (1) in Table 1) with those who receive any advice (groups (2)–(4)) identifies the overall effect of receiving advice, irrespective of its specific form. Second, comparisons across the four treatment arms allow us to separately identify the effects of occupational recommendations, vacancy information, and their combination. Third, exogenous variation in treatment intensity across municipalities enables us to test for treatment spillovers on untreated job seekers by comparing outcomes of control-group individuals in super-control, medium-intensity, and high-intensity regions. Finally, comparing outcomes of treated job seekers across medium- and high-intensity regions allows us to assess whether advice leads to spillover effects among treated individuals.

2.3 Procedures, data, and sample statistics

All individuals who were registered as unemployed and received UI benefits on March 17, 2019 were randomly assigned to either the control group or one of the 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 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 combination of different data sources, which can be linked at the individual level. First, we exploit comprehensive register data administered by Statistics Denmark on socio-demographic characteristics and individuals' labor market outcomes. For all participants in our experiment, we observe monthly measures of employment status, working hours, labor earnings, and occupations, as reported by their employers to the tax authorities, for up to 12 months after the start of the intervention.[6] Second, we use information from job seekers' personal job search profiles and from the vacancy database on the job search platform administered by the public employment service. This allows us to trace the exact information to which job seekers were exposed during the intervention. Finally, to study job search behavior, we analyze data on individuals' job applications. Specifically, while receiving unemployment benefits, individuals are required to actively search for and apply to jobs and to document their search activities in a centralized online system (*joblog*). The information reported includes the job title as well as the name and address of the prospective employer (see Fluchtmann *et al.*, 2024, for further details). The application data also include an identifier for the occupation associated with each application, allowing for direct comparison with the occupations stored in individuals' search profiles and those recommended by our algorithm. While UI recipients are not restricted in the range of occupations they can apply to, they must document at least two applications per week.[7]

Appendix Table A.1 provides an overview of participants' background characteristics, separated by treatment status and treatment-intensity regime. Job seekers in our experiment are on average 40 years old, about 53% are female, 35% are married or cohabiting, and 36% have a university degree. On average, they are unemployed for about six months, had a gross monthly labor income of roughly DKK 18,500 (approx. € 2,500), and worked around 19 hours per week in the previous year (including periods of non-employment). Comparing the characteristics of treated and non-treated individuals across the different intensity regimes shows that the two-stage randomization was

[6] Notably, the first COVID-19 lockdown in Denmark began on March 13, 2020. Hence, our results should not be affected by labor market disruptions related to the COVID-19 pandemic.

[7] Fluchtmann *et al.* (2024) show that the application data provide valuable insights into how job seekers allocate their search across different occupations. However, as compliance with the requirement is high, the number of registered applications may not accurately represent job seekers' actual search intensity.

successful, with only minor differences between groups. Nonetheless, we condition on a rich set of covariates in all empirical specifications.

3 Theoretical Framework

Before presenting the results of our experiment, we outline the potential direct and indirect effects of advice within an occupational search framework (see also Belot *et al.*, 2019; Kircher, 2022). First, we examine how occupational recommendations and vacancy information affect job seekers' search behavior and employment prospects, and how their combination may amplify or offset their individual effects. Second, we discuss how job seekers' behavioral responses to advice may generate spillover effects for other job seekers.

We consider an economy with a population N of unemployed job seekers, categorized into different types $i \in \{1, ..., I\}$, who decide how to allocate their total search effort, $s_i \geq 0$, across different occupations $k \in \{1, ..., K\}$. For a job seeker of type i, the effort dedicated to seeking employment in occupation k is given by s_{ik}. Job seekers vary in how well their skills align with the requirements of various occupations; the skill alignment between job seeker i and occupation k is represented by $\phi_{ik} \in [0, 1]$.

The overall number of job matches that occur in a specific occupation k are characterized by the matching function, $m(u_k, v_k)$. This function is increasing and concave in the number of posted vacancies, v_k, and in the effort exerted by all job seekers searching for jobs in k, $u_k = \sum_i^N s_{ik}$ (see, e.g., Pissarides, 2000; Michaillat, 2012; Crépon *et al.*, 2013). The occupation-specific labor market conditions are summarized by the tightness $\theta_k = v_k/u_k$. Given this, the probability that a job seeker of type i exerting search effort s_{ik} receives a job offer in occupation k is given by:

$$\lambda_{ik} = \phi_{ik} s_{ik} m(u_k, v_k)/u_k = \phi_{ik} s_{ik} q(\theta_k), \tag{1}$$

where the function $q(\theta_k)$ is increasing and concave in θ_k. Searching for a job in occupation k creates costs denoted by $\gamma(s_{ik}, s_{i-k})$, which are convex in effort (s_{ik}, s_{i-k}) and feature crowding across occupations: higher effort devoted to one occupation increases the marginal cost of exerting effort in other occupations ($\partial^2\gamma/\partial s_{ik}\partial s_{i-k} > 0$). The value of employment in occupation k for a job seeker of type i is represented by $V_{ik}(\phi_{ik}, \theta_k)$. This value increases with the alignment between the worker's skills and the job requirements of occupation k, ϕ_{ik}, as well as with the occupation-specific labor market tightness, θ_k. The latter reflects that workers can negotiate for improved job characteristics, such as higher wages or more stable employment, when facing less competition from other workers within the same occupation. Finally, the instantaneous utility derived from unemployment is represented by b.

Job seekers maximize the present value of income over an infinite horizon, with discount rate ρ and U_i denoting the value of being unemployed for worker of type i:

$$\rho U_i = \max_{s_1,\dots,s_K} \left[b + \sum_k \left\{ \lambda_{ik}(\phi_{ik}, s_{ik}, \theta_k) \max\left\{ V_{ik}(\phi_{ik}, \theta_k) - U, 0 \right\} - \gamma(s_{ik}, s_{i-k}) \right\} \right], \tag{2}$$

where the right-hand side captures the flow utility from unemployment (b), plus the chance of receiving an offer from occupation k at rate λ_{ik} multiplied by the gain in value associated with a potential offer ($V_{ik} - U$, if this is positive) net of search costs ($\gamma(\cdot)$). The optimal search strategy is characterized by the effort vector $s^* = (s_1^*, ..., s_K^*)$, which trades off the costs of effort against its returns across the various occupations. The optimal search strategy is derived from the first-order conditions with respect to search effort s_{ik} that a job seeker of type i allocates to occupation k:

$$\phi_{ik} q(\theta_k) \max\left\{ V_{ik} - U_i, 0 \right\} = \frac{\partial \gamma(s_{ik}, s_{i-k})}{\partial s_{ik}}. \tag{3}$$

The left-hand side of Equation (3) represents the marginal benefit of search effort in occupation k, which increases with skill alignment, labor market tightness, and the surplus from a job offer in occupation k. The right-hand side captures the marginal cost of exerting effort in occupation k, given the total search effort across all other occupations, s_{i-k}. For any occupation k in which the job seeker exerts positive effort ($s_{ik} > 0$), the marginal return to search must equal its marginal cost. In occupations where the marginal return at zero effort is lower than the marginal cost, the optimal search effort is zero, implying a corner solution. An increase in the occupation-specific tightness θ_k or skill alignment ϕ_{ik} raises the marginal return to search in occupation k, thereby increasing optimal effort s_{ik}. Because search costs exhibit cross-occupation crowding, higher effort in occupation k raises the marginal cost of searching elsewhere and crowds out effort in other occupations, leading to a reduction in s_{i-k}.

3.1 Redirecting job search across occupations

The primary objective of advice in our experiment is to support job seekers in making informed decisions about how to allocate their search efforts across occupations, thus potentially improving their labor market prospects. We assume that job seekers hold subjective beliefs about their personal skill alignment with each occupation, $\widehat{\phi}_{ik}$, and about the occupation-specific labor market tightness, $\widehat{\theta}_k$, and maximize their utility based on these subjective beliefs.

In this subsection, we illustrate how the specific forms of advice provided in our experiment may alter job search behavior and labor market prospects if job seekers update their subjective beliefs. In Section 3.2, we then turn to discussing how the associated shifts in job seekers' occupational search strategy may induce externalities on other market participants. For illustrative purposes, our discussion concentrates on a scenario with only two occupations $k \in \{1, 2\}$ and two types of workers $i \in \{1, 2\}$, where the type corresponds to the job seeker's core occupation as specified in their search profile at the onset of the experiment.[8] In the presentation of our examples, we closely follow Kircher (2022).

Improving skill alignment: We begin by illustrating the potential impact of occupational recommendations. Consider a scenario in which labor market tightness is equal across occupations ($\theta_2 = \theta_1$), and type-1 workers initially search more intensively in occupation 1 ($s_{11} > s_{12}$) because they believe their skill alignment is higher in occupation 1 than in occupation 2 ($\widehat{\phi}_{11} > \widehat{\phi}_{12}$). Moreover, suppose they underestimate how well their skills align with occupation 2 relative to the true degree of skill alignment for this occupation ($\widehat{\phi}_{12} \leq \phi_{12}$). For instance, occupation 1 may be their previous occupation, and job seekers might be unaware that their skills also align well with occupation 2.

The occupational recommendation prompts job seekers to update their beliefs about skill alignment. This means that type-1 workers who receive a recommendation for occupation 2 may learn that their skills are better aligned with that occupation than they initially believed. As a result, they redirect their search effort accordingly, potentially enhancing their job finding prospects (through λ) and improving the quality of job

[8] Consistent with our empirical setting, job seekers may search both within and outside their core occupations, i.e., s_{i1} and s_{i2} may both be positive. We assume that, in the absence of receiving advice, job seekers exert the highest search effort in their core occupation, i.e., $s_{11} \geq s_{12}$ and $s_{22} \geq s_{21}$.

matches (through V). If job seekers follow the recommendations directly, additional employment will primarily occur in the occupations recommended to them.

Equalizing labor market conditions: In the context of our framework, we interpret the provision of vacancy information as a proxy for informing job seekers about occupation-specific labor market tightness (see Section 2.1). To illustrate the potential effects of receiving vacancy information, consider a scenario in which job seekers are equally qualified for both occupations (i.e., for type-1 job seekers, $\phi_{11} = \phi_{12}$). Suppose that in the absence of advice, job seekers predominantly search within their own occupation type (i.e. for type-1 job seekers, $s_{11} > s_{12}$, and for type-2 job seekers $s_{22} > s_{21}$), because they initially expect labor market tightness to be higher in their own occupation (i.e., for type-1 job seekers, $\widehat{\theta}_1 > \widehat{\theta}_2$, and for type-2 job seekers, $\widehat{\theta}_2 > \widehat{\theta}_1$). Furthermore, let both types misperceive the true labor market tightness of their core occupation. For sake of illustration, let type-1 job seekers overestimate it ($\widehat{\theta}_1 > \theta_1$) and type-2 job seekers underestimate it ($\widehat{\theta}_2 < \theta_2$).

In this scenario, job seekers of type 1 are overly optimistic regarding the employment opportunities in their own occupation, whereas type-2 job seekers are overly pessimistic. Vacancy information leads job seekers to update their beliefs about the occupation-specific tightness, encouraging them to redirect their search efforts accordingly. If type-1 workers learn that the number of vacancies is lower than they thought, they may infer that θ_1 is lower than anticipated. As a consequence, they shift search effort from occupation 1 to occupation 2. All else being equal, this adjustment increases their job finding prospects (through λ) and improves the job quality (through V). For type-1 job seekers who initially overestimate the tightness in their own occupation, the vacancy information will create additional employment *outside* their core occupations. On the other hand, upon receiving vacancy information, job seeker of type-2 may infer that θ_2 is higher than initially believed, causing a shift in search effort from occupation 1 to occupation 2. This adjustment can also improve labor market outcomes, with additional employment occurring in the *core* occupations of job seekers.

Complementarities of search advice: Vacancy information and occupational recommendations can have complementary effects if they provide consistent signals. Consider a scenario in which type-1 job seekers initially search too intensively in occupation 1 (i.e., $s_{11} > s_{12}$), because they overestimate the labor market tightness in occupation 1 ($\widehat{\theta}_1 > \theta_1$) and underestimate their skill alignment with occupation 2 ($\widehat{\phi}_{12} < \phi_{12}$).

Upon receiving vacancy information indicating that occupation 1 has fewer openings than initially believed, the job seekers may revise their expectations and shift search effort toward occupation 2. If they also receive recommendations suggesting that their skills are better aligned with occupation 2 than they previously thought, this further reinforces the shift. The combined effect of lower-than-expected vacancy availability in occupation 1 and better-than-expected skill alignment in occupation 2 can amplify their behavioral response, resulting in a more substantial reallocation of search effort across occupations.[9]

In contrast, when both types of advice provide conflicting signals, their individual effects can offset each other, resulting in a muted behavioral response. For example, consider a scenario in which type-2 job seekers are overly pessimistic about labor market tightness in their core occupation ($\widehat{\theta}_2 < \theta_2$) and underestimate their skill alignment with occupation 1 ($\widehat{\phi}_{21} < \phi_{21}$). Suppose they receive vacancy information indicating that occupation 2 has more openings than expected, while simultaneously being recommended to consider occupation 1 due to a better-than-expected skill alignment. Faced with these opposing signals—greater opportunity in occupation 2 versus better fit in occupation 1—job seekers may experience ambiguity about how to adjust their search. If the marginal costs of reallocating their search effort are sufficiently high, they may ultimately decide to maintain their existing strategy, exhibiting only a limited or no response to the new information.[10]

Summary: Overall, the discussion in this section illustrates that personalized job search advice—whether through occupational recommendations or vacancy information—can improve labor market outcomes by helping job seekers better allocate their search efforts across occupations. Occupational recommendations may prompt individuals to reassess their skill alignment with alternative occupations, while vacancy information may lead them to update their beliefs about labor market tightness. In both cases, the resulting

[9] With more than two occupations, receiving both vacancy information and occupational recommendations may help job seekers update their perceptions of labor demand in their core occupations and guide them toward those alternative occupations that exhibit the highest skill alignment.

[10] In principle, job seekers might increase their overall effort in such a scenario. However, if marginal search costs are high, this response is unlikely. In an extreme case, total search effort could be fixed, with costs being zero up to a certain point and becoming infinite beyond that.

reallocation of search effort has the potential to increase job finding rates and improve match quality. When provided jointly, the two types of advice can reinforce each other when they point in the same occupational direction, or offset each other when they provide conflicting signals.

3.2 Externalities on other job seekers

The discussion in the previous section illustrates how advice can lead job seekers to reallocate search effort across occupations, with treated job seekers shifting some search effort from occupation 1 to occupation 2 in our illustrative examples. However, as more individuals receive advice and adjust their search activities accordingly, this generates externalities that affect other job seekers, with differing impacts on those who receive the treatment and those who do not.

Externalities on treated job seekers: As more job seekers receive advice and redirect their search efforts accordingly, the labor market tightness in the absorbing market (occupation 2 in the scenarios described above), θ_2, decreases. This implies that treated type-1 job seekers who shift to occupation 2 experience weaker employment effects if the proportion of treated individuals increases. Consequently, the effectiveness of advice should be lower in regions with a high treatment intensity compared to medium-intensity regions.

Externalities on non-treated job seekers: The sign of treatment spillovers on non-treated job seekers depends on how the intervention alters the labor market tightness in their core occupations. Non-treated type-2 job seekers, who predominantly search in occupation 2, are negatively affected by the increased competition as the share of treated individuals who shift effort to occupation 2 increases. Conversely, non-treated type-1 job seekers may benefit from a higher treatment intensity, as the labor market tightness in their core occupation, θ_1, increases when more and more treated job seekers shift towards occupation 2. As a result, labor market prospects for untreated type-1 job seekers improve as treatment intensity increases.

Moreover, the externalities experienced by untreated job seekers may also vary depending on whether the initial tightness is equal across occupations or not. This follows from the concavity of the matching function, suggesting that the number of matches is maximized when the tightness is equalized across occupations (see also Şahin *et al.*, 2014; Kircher, 2022). If initially $\theta_2 \gg \theta_1$, redirecting type-1 job seekers to occupations 2 improves labor market prospects for those continuing their search in occupation 1, while the additional congestion in occupation 2 remains relatively modest. Conversely, if $\theta_2 = \theta_1$, so that the initial allocation is closer to the efficient benchmark, redirecting workers offers less relief, and the congestion caused by a larger proportion of treated individuals becomes more severe.

Summary: Assuming that advice encourages treated job seekers to reallocate their search effort across occupations, the framework yields three testable predictions about treatment spillovers in our setting. First, higher treatment intensity leads to negative indirect effects among treated job seekers. Hence, the labor market outcomes for treated individuals should be relatively worse as the number of treated job seekers increases. Second, spillover effects on non-treated job seekers depend on whether advice increases or reduces competition in their core occupations. Specifically, higher treatment intensity should lead to improved labor market outcomes for non-treated job seekers whose core occupations face reduced competition, whereas outcomes should be worse for those whose core occupations experience increased competition from treated individuals. Third, labor market outcomes for untreated job seekers depend on the distribution of initial labor market tightness across occupations within a region: they should improve when tightness is relatively unequally distributed and worsen when tightness is relatively equally distributed at the onset of the intervention.

3.3 Inducing more search

Advice may not only encourage job seekers to redirect their search effort but also to intensify it. When increases in the perceived occupation-specific tightness or skill alignment raise expected returns by more than marginal search costs, the resulting adjustment need not crowd out effort in other occupations one-for-one and may instead lead treated job seekers to expand their overall search effort. Such an expansion may directly enhance their reemployment prospects but could also lead to indirect effects by reducing labor market tightness in both occupations. Consequently, both treated and non-treated job seekers may experience worse employment outcomes in high-intensity regions compared to medium-intensity regions. Unlike the previous cases, however, this scenario implies only negative spillover effects, such that non-treated job seekers would generally not benefit from an increase in the proportion of treated individuals.

4 Direct and Indirect Effects of Advice

Building on these theoretical insights, the first part of our empirical analysis examines the direct and indirect effects of online job search advice, considering the different forms of advice jointly. Specifically, we compare labor market outcomes of treated and untreated job seekers in regions with higher vs. lower treatment intensity, aggregating across the three treatment arms described in Section 2.2. We estimate interacted regressions of the following form:

$$Y_{ij} = \delta \textsc{Advice}_i + \gamma(\textsc{Advice}_i \times TI_j^{\text{High}}) + \alpha_M TI_j^{\text{Med}} + \alpha_H TI_j^{\text{High}} + X_i \Pi + \varepsilon_{ij}, \tag{4}$$

where $\textsc{Advice}_i$ denotes whether individual i is assigned to any of the three treatment groups receiving personalized advice, while TI_j^{Med} and TI_j^{High} indicate whether municipality j is assigned to the medium-intensity regime or the high-intensity regime, respectively. X_i is a vector of pre-intervention control variables including age, gender, education, labor market histories, unemployment duration and dummies for the ten regional strata identifying municipalities with similar local labor market characteristics. Standard errors are clustered at the municipality level.

Throughout our empirical analysis, we focus on three main outcome variables Y_{ij} to assess the labor market effects of the intervention. First, we examine the average monthly employment rate—measured as the number of months each job seeker is employed over a given time horizon—to capture employment incidence over time. Second, we consider cumulative hours worked, and third, total labor earnings, both aggregated over the same horizons, to capture intensive-margin employment and earnings effects. In addition, to shed light on shifts in search and occupational competition, we analyze job seekers' application behavior using administrative data on registered job applications (see Section 2.3).

The coefficient δ captures the effect of receiving advice relative to the control group in regions assigned to the medium-intensity regime. Since 60% of job seekers in these regions receive some form of advice, δ reflects a combination of direct effects and any indirect effects that may arise at this intermediate intensity level.[11] In contrast, the coefficient γ measures how treatment effects differ between job seekers in the high-intensity regime and those in the medium-intensity regime. A positive (negative) γ implies positive (negative) treatment spillovers among treated job seekers. Lastly, α_M and α_H capture the effects of residing in a region assigned to the medium-intensity or high-intensity regime, respectively, relative to the super-control group. Positive (negative) α-coefficients therefore indicate positive (negative) treatment spillovers on untreated job seekers.

By varying the share of treated individuals at the municipality level, we assume that job seekers residing within the same municipality are more likely to compete for the same vacancies. While this assumption is intuitive, job seekers may naturally not restrict their search exclusively to their municipality of residence. As a result, treatment spillovers may extend beyond municipal boundaries. We therefore also examine the robustness of our findings using several alternative definitions of local labor markets.

4.1 Labor market effects of advice

Table 3 presents our main results, examining the average monthly employment rate, total working hours, as well as total labor earnings accumulated over horizons of six and twelve months.

Treatment effects: Receiving advice improves labor market outcomes for treated job seekers when the proportion of treated individuals remains moderate. In regions assigned to the medium-intensity regime, treated job seekers exhibit significantly higher levels of employment and earnings than the control group. In the first six months after the beginning of the intervention, the average monthly employment rate of treated individuals is approximately 0.9 percentage points higher ($p = 0.034$), corresponding to a 2.1% increase in employment relative to the baseline employment rate of control-group job seekers in super-control regions. We further observe that treated job seekers in medium-intensity regions work about 8.8 additional hours (+2.6%; $p = 0.010$) and earn DKK 1,858 more (+3.0%; $p = 0.006$) than their non-treated counterparts. Overall, these

[11] Note that, in the presence of economically relevant treatment spillovers, a "pure" direct effect of the intervention could only be identified when the share of treated job seekers is very small.

results indicate that online job search advice has positive effects on the labor market integration of unemployed workers.

Turning to longer-term outcomes, we continue to observe sizable and statistically significant positive impacts on cumulative working hours and earnings. Over a 12-month horizon, treated job seekers accumulate 1.4% more working hours ($p = 0.052$) and 1.8% higher earnings ($p = 0.016$), respectively. At the same time, the longer-term effect on the average monthly employment rate is not statistically significant at conventional levels.

Table 3: Direct and indirect effects of advice

Dependent variable	Avg. monthly employment rate in %-points		Total working hours		Total labor earnings in DKK	
	6m. (1)	12m. (2)	6m. (3)	12m. (4)	6m. (5)	12m. (6)
ADVICE (δ)	0.88**	0.45	8.75**	11.03*	1,858***	2,626**
	(0.41)	(0.31)	(3.35)	(5.60)	(667)	(1,074)
$\times$ high-intensity (γ)	-1.61**	-0.79	-12.21**	-10.73	-3,384***	-4,203*
	(0.62)	(0.59)	(5.09)	(10.68)	(1,058)	(2,134)
Treatment intensity regime (ref. super-control)						
Medium-intensity (α_M)	-0.60	-0.50	-3.95	-9.03	31	365
	(1.05)	(0.80)	(8.06)	(11.71)	(1,414)	(2,058)
High-intensity (α_H)	0.94	0.58	4.40	2.63	2,055	3,188
	(1.02)	(0.89)	(7.98)	(14.16)	(1,368)	(2,244)
P-value ($\alpha_M = \alpha_H = 0$)	0.322	0.403	0.619	0.615	0.279	0.359
No. of observations	92,098	92,098	92,098	92,098	92,098	92,098
Mean dep. variable (super-control)	41.67	47.00	338.2	787.5	62,116	145,013
Control variables						
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Market-strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports the results of interacted regressions of treatment indicators and local treatment intensity regime dummies as described by Equation (4) estimated for the full experimental population. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level.

Treatment spillovers: Comparing job seekers across regions with different treatment intensities yields two main findings. First, the positive effects of advice decline as the share of treated individuals increases. As indicated by the negative interaction coefficients (γ), treated job seekers in high-intensity regions exhibit lower levels of employment, working hours, and earnings than those receiving advice in medium-intensity regions. These negative spillover effects are most pronounced during the first six months, but the

γ-coefficients remain consistently negative throughout the observation period. Overall, these results demonstrate that advice generates negative spillovers among treated job seekers. Comparing the treatment coefficients (δ) and the interaction terms (γ) indicates that these spillover effects can fully offset the positive effects of advice at high treatment intensities.

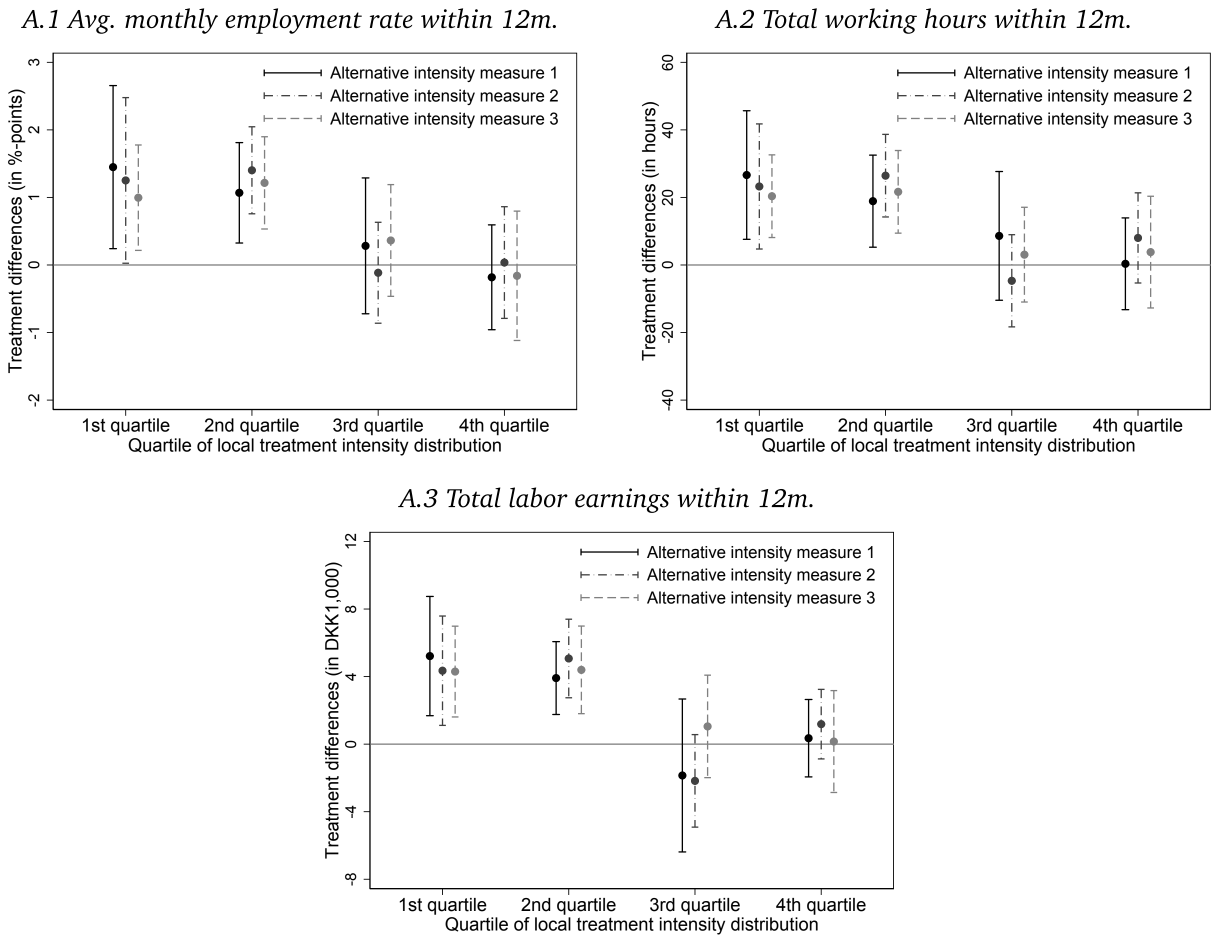
Second, we find no statistically significant average spillover effects on the labor market outcomes of untreated job seekers. Although untreated individuals in high-intensity regions exhibit slightly higher employment and earnings than those in the super-control group, these differences are not statistically significant (all α-coefficients are insignificant). We return to this issue in Section 4.3, where we examine heterogeneity in the spillover effects on untreated job seekers.

Alternative definitions of local labor markets: Our experiment exogenously varies the share of treated individuals at the municipality level. To assess the robustness of our findings, we also consider several alternative definitions of local labor markets. Specifically, we construct three continuous measures of local treatment intensity that reflect (1) the number of treated job seekers in neighboring municipalities, (2) commuting flows within the Danish labor market, and (3) job seekers' allocation of applications across regions and occupations before the intervention. Details on the construction of these measures, together with evidence on their validity—namely, that they are uncorrelated with job seekers' background characteristics—are provided in Appendix B. These alternative measures serve a dual purpose. First, they allow us to assess the sensitivity of our results to different definitions of local labor markets, acknowledging that job seekers may search beyond their municipality of residence and that treatment spillovers may extend across administrative boundaries. Second, the continuous measures enable us to explore a wider range of treatment intensities across local labor markets—ranging from 10–90% for the first measure and from roughly 30–80% for the second and third (see Appendix Figure B.1).[12]

For each of the three alternative measures of treatment intensity, Figure 1 displays treatment effects on our three main outcomes—measured over a 12-month time

[12] As discussed above, a pure direct treatment effect can only be identified when the share of treated job seekers within a local labor market is very small; the alternative definitions considered here imply lower effective treatment intensities in some regions under different assumptions about the scope of search.

Figure 1: Treatment effects for alternative treatment-intensity measures



Note: The figure depicts treatment effects (with 90% confidence intervals) on average monthly employment rates, total working hours, and total labor earnings over the first 12 months after the start of the intervention, comparing treated individuals receiving any form of advice to the control group. Treatment effects are estimated across quartiles of three alternative treatment-intensity distributions. **Alternative intensity measure 1:** the share of treated individuals within a job seeker's own municipality and all adjacent municipalities. **Alternative intensity measure 2:** the share of treated individuals in all municipalities, weighted by the proportion of commuters between the job seeker's municipality of residence and all other municipalities. **Alternative intensity measure 3:** the share of treated job seekers applying to the same local labor market, defined by the combination of zip-code areas and 3-digit occupations. See Appendix B for further details on the construction of the alternative intensity measures.

horizon—across quartiles of the respective treatment-intensity distributions. The results closely mirror our main findings from Table 3. We consistently find positive labor market effects of advice when the share of treated individuals is relatively low: across all measures, individuals in the bottom two quartiles experience a 2–4% increase in employment, working hours, and earnings over one year. In contrast, we find no significant treatment effects in the upper two quartiles. Appendix Figure B.2 further shows that treatment intensity is unrelated to the average labor market outcomes of untreated individuals, whereas higher intensities are associated with weaker outcomes among treated individuals. Taken together, these results reinforce the conclusion that advice improves job seekers' labor market prospects when the share of treated individuals is limited, but that its positive effects decline as the intervention is extended to a larger share of job seekers.

4.2 Shifts in occupational competition

In a next step, we explore the mechanisms underlying the observed treatment spillovers. As discussed in Section 3.2, negative spillover effects may arise if treated individuals redirect their search, increasing the concentration of job seekers in certain local labor markets. This heightened competition for specific jobs can lead to congestion effects, ultimately hindering labor market integration. To examine the relevance of this mechanism, we use data on registered job applications and available vacancies from the online platform (see Section 2.3) to construct a measure of competition at the occupational level, defined as the average number of applications per vacancy in each occupation. For each job seeker, we then compute the log average number of applications per vacancy across the set of occupations to which the individual applies in different time intervals following the start of the intervention. Using this measure as the dependent variable, we estimate the same regression specification as in Equation (4). This approach allows us to shed light on how occupation-specific competition evolves for treated and untreated job seekers across different treatment-intensity regimes, capturing both direct effects of job seekers shifting their search across occupations and the resulting indirect effects on competition.

Column (1) of Table 4 shows the corresponding estimates when considering all applications registered within the first four weeks after the start of the intervention. The observed patterns mirror the effects on labor market outcomes documented in the previous section. First, treated job seekers in medium-intensity regions apply to occupations in which they face significantly less competition than their untreated counterparts (see the negative δ-coefficient), consistent with the positive labor market effects of advice in these regions. Second, the effects on occupational competition reverse as the treatment intensity increases. As indicated by the positive γ-coefficient, treated individuals in high-intensity regions apply to occupations characterized by significantly greater competition, i.e., a higher number of applicants per vacancy. This pattern supports the interpretation

Table 4: Shifts in occupational competition

Dependent variable	Log average no. of applications per vacancy in occupations applied to$^{(a)}$		
	1m.	6m.	12m.
	(1)	(2)	(3)
ADVICE (δ)	-0.048**	-0.059**	-0.033
	(0.021)	(0.028)	(0.026)
$\times$ high intensity (γ)	0.114**	0.067	0.025
	(0.051)	(0.048)	(0.049)
Treatment intensity regime (ref. super-control)			
Medium intensity (α_M)	0.031	-0.056	-0.076
	(0.084)	(0.080)	(0.080)
High intensity (α_H)	-0.068	-0.050	-0.049
	(0.092)	(0.079)	(0.078)
P-value ($\alpha_M = \alpha_H = 0$)	0.449	0.758	0.640
No. of observations	82,957	85,994	87,606
Control variables			
Individual characteristics	Yes	Yes	Yes
Market-strata fixed effects	Yes	Yes	Yes

Note: The table reports the results of interacted regressions of treatment indicators and local treatment intensity regime dummies as described by Equation 4 for the full experimental population. 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 is the average number of applications, normalized by the number of available vacancies, across the occupations each job seeker applied to within one, six, or twelve months after the start of the intervention.

that negative spillovers among treated job seekers arise from congestion effects: as more individuals redirect their search effort in response to the intervention, they increasingly target similar occupations, leading to congestion within those labor markets. Third, as indicated by the insignificant α-coefficients, the results suggest that the intervention does not systematically affect the average level of competition faced by job seekers in the control group. At the same time, for control job seekers in high-intensity regions, the corresponding coefficients are persistently negative, suggesting that some untreated individuals may experience reduced competition as more treated job seekers redirect their search. We explore the heterogeneity in spillover effects on untreated job seekers in the next section. Finally, when examining applications over six- and twelve-month horizons (see columns (2) and (3) of Table 4, respectively), the overall pattern remains qualitatively similar but attenuates over time, with smaller estimates and no statistically significant effects at the twelve-month horizon.

4.3 Externalities on non-treated job seekers

While our results so far indicate that, on average, the labor market outcomes of untreated job seekers are not affected by the intervention, the framework discussed in Section 3 suggests that treatment spillovers on untreated job seekers may vary systematically across subgroups of control job seekers. In particular, the impact on untreated job seekers is expected to depend on (1) how the intervention changes labor market tightness in the occupations they target, and (2) whether initial tightness is unevenly or evenly distributed across occupations within a region. In this subsection, we empirically test these two hypotheses.

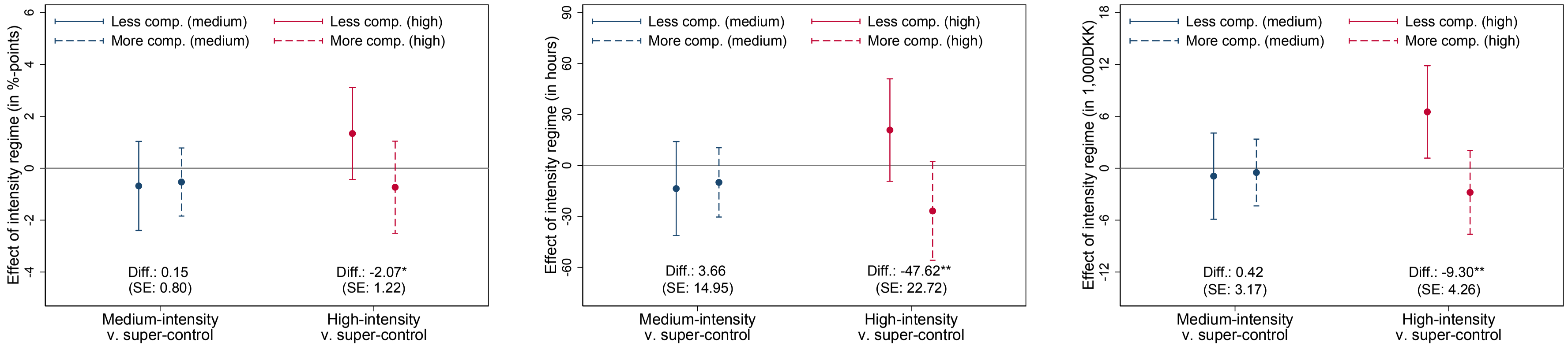
Heterogeneity by change of competition: First, we examine how changes in competition in the core occupations of control job seekers shape treatment spillovers. We measure changes in occupational competition by comparing the number of applications by treated job seekers to a given occupation at the national level in the post-intervention period relative to the pre-intervention period. We focus on applications from individuals in the treatment groups and consider three-month windows before and after the start of the experiment. Based on this measure, whose distribution is depicted in Appendix Figure A.4, we distinguish between untreated job seekers (i) who experience relatively less competition in their core occupations and (ii) those who experience more competition from treated job seekers as treatment intensity rises.

Panel A of Figure 2 shows that spillovers on untreated job seekers—induced by higher treatment intensity—depend systematically on how the intervention alters competition in their core occupations. Spillover effects of the high treatment-intensity regime tend to be positive for untreated job seekers whose core occupations experience reduced competition from treated job seekers, but negative for those whose core occupations become more crowded (cp. red solid and dashed lines in Panel A of Figure 2). The differences in spillover effects across less vs. more competitive occupations are statistically significant for all three outcomes—employment rates, working hours, and earnings—with p-values of 0.093, 0.039, and 0.032, respectively. To illustrate the magnitude of these differences, untreated job seekers facing reduced competition in high-intensity regions experience an increase in total labor earnings of roughly DKK 6,000 relative to super-control group job seekers targeting the same core occupations, whereas those whose core occupations be-

Figure 2: Heterogeneous spillover effects on the control group

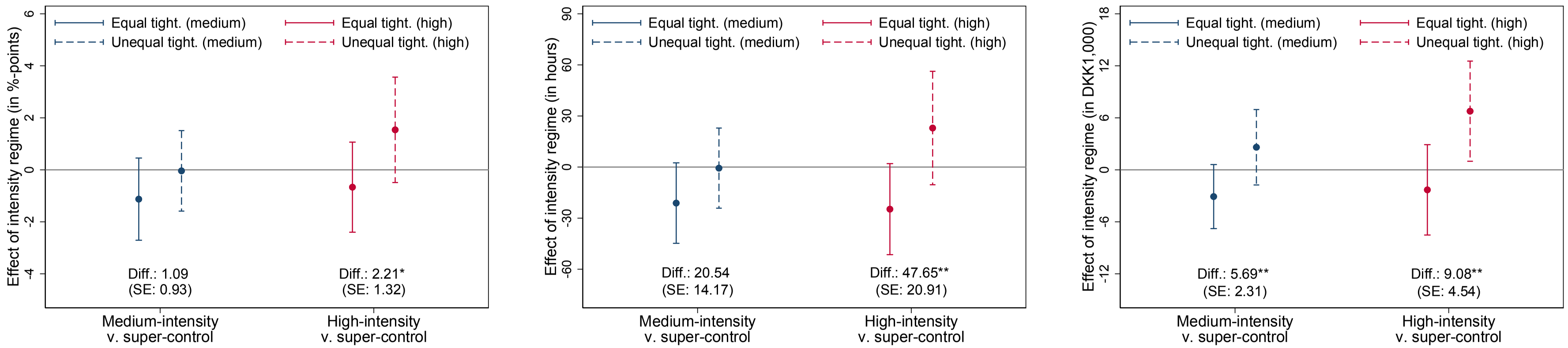
A. Heterogeneity by change of competition in core occupations

A.1 Avg. monthly employment rate within 12m. *A.2 Total working hours within 12m.* *A.3 Total labor earnings within 12m.*



B. Heterogeneity by variance of labor market tightness

B.1 Avg. monthly employment rate within 12m. *B.2 Total working hours within 12m.* *B.3 Total labor earnings within 12m.*



Note: The figure shows treatment spillovers—i.e., the effects of being assigned to the medium- or high-intensity regime (with 90% confidence intervals)—on control-group job seekers across different labor-market segments. All specifications include individual controls and market-strata fixed effects, and standard errors are clustered at the municipality level. The blue dots and lines show differences between the medium-intensity regime and the super-control group, while the red dots and lines show differences between the high-intensity regime and the super-control group.
Panel A: We divide the sample based on the change in competition within job seekers' core occupations (averaged across all core occupations). This measure is constructed using the change in the number of applications submitted to each occupation—comparing the three months before and after the intervention—by individuals in the treatment groups. We distinguish between control-group job seekers who are predicted to face less competition (solid lines) and more competition (dashed lines) from treated job seekers.
Panel B: We divide the sample based on the variance in labor-market tightness across occupations within a municipality. Tightness is measured using the number of posted vacancies in each municipality-occupation combination and the number of job seekers residing in the municipality who list that occupation in their initial search profile. Using a median split of the variance measure, we distinguish between job seekers in municipalities with a relatively equal (solid lines) or unequal (dashed lines) tightness distribution.

come more crowded exhibit a mild decline in earnings (Panel A.3). Qualitatively similar patterns emerge for employment rates and working hours. Overall, these results indicate that spillovers on untreated job seekers in high-intensity regions are heterogeneous and operate through changes in occupation-specific competitive pressure.

When comparing untreated job seekers in medium-intensity regions to the super-control group, we observe no systematic differences in spillovers, independent of whether competition in their core occupations increases or decreases. This suggests that, at intermediate treatment intensities, changes in occupational competition do not translate into differential spillover effects on the control group. A possible interpretation of this pattern is that shifts in search effort do not generate systematic changes in competitive pressure for untreated job seekers at intermediate treatment intensities. This finding complements the evidence in Figure 1, which indicates that economically relevant spillover effects on treated job seekers emerge primarily at relatively high treatment intensities.

Heterogeneity by variance of initial tightness: Second, we examine whether treatment spillovers vary depending on whether initial tightness is evenly or unevenly distributed across occupations within a region. This analysis is motivated by the theoretical argument that congestion effects should be weaker when initial tightness is uneven across occupations—a consequence of the concavity of the matching function. To operationalize this idea, we calculate the variance of occupation-specific tightness in each municipality and split the sample at the median of this distribution.

Panel B of Figure 2 shows that treatment spillovers on untreated job seekers differ systematically depending on whether initial labor market tightness is uneven or evenly distributed across occupations within a region. The spillover effects of the high treatment-intensity regime on labor market outcomes for untreated job seekers in regions with unequal initial tightness are more favorable than for their counterparts in regions with more evenly distributed tightness. The observed differences are statistically significant for employment rates, working hours, and earnings in high-intensity regions ($p = 0.097$, $p = 0.025$, and $p = 0.044$, respectively). In regions with medium treatment intensity, differences are qualitatively similar, though generally not statistically significant. Overall, these findings are in line with the notion that redirecting treated job seekers can alleviate congestion when initial labor market conditions are rather unequal across occupations.

Summary: Overall, the empirical patterns are consistent with the idea that treatment spillovers arise as treated job seekers reallocate their search effort across occupations. As the share of individuals receiving advice increases, labor market outcomes deteriorate for treated job seekers (Table 3 and Figure 1), and we observe heterogeneous spillover effects on untreated job seekers, depending on changes in occupation-specific competition and the initial distribution of occupation-specific tightness (Figure 2). An alternative mechanism discussed in Section 3.3 is that spillovers arise because treated job seekers increase their overall search intensity. Under this mechanism, however, we would not expect some untreated job seekers to benefit from an increase in the number of treated individuals, as labor market tightness in their core occupations would remain largely unchanged. Taken together, the evidence presented in this section thus points to a reallocation of search effort across occupations as a central channel through which treatment spillovers operate.

5 Effects of Different Types of Advice

Thus far, our analysis has focused on the overall direct and indirect effects of online job search advice. In the remainder of the study, we examine the effects of different types of advice separately. Specifically, we estimate specifications analogous to Equation (4), allowing treatment effects to differ across the three treatment arms depicted in Table 1: the recommendation treatment, the vacancy treatment, and the combined treatment. Table 5 reports the effects on average monthly employment rates, total working hours, and labor earnings accumulated over six and twelve months following the start of the intervention.

We find that both the recommendation and vacancy treatments improve labor market outcomes for treated job seekers at intermediate treatment intensities. During the first six months of the experiment, job seekers assigned to the *recommendation treatment* in medium-intensity regions experience a 1.1 percentage-point higher monthly employment rate ($p = 0.005$), work approximately 10 additional hours ($p = 0.003$), and earn DKK 2,356 more ($p < 0.001$) than their counterparts in the control group. These effects

Table 5: Direct and indirect effects of different types of job search advice

Dependent variable	Avg. monthly employment rate in %-points		Total working hours		Total labor earnings in DKK	
	6m. (1)	12m. (2)	6m. (3)	12m. (4)	6m. (5)	12m. (6)
Recommendation treatment (δ_{Rec})	1.10***	0.32	10.05***	7.32	2,356***	2,560*
	(0.39)	(0.37)	(3.33)	(7.28)	(679)	(1,538)
× high intensity (γ_{Rec})	-1.99***	-0.98	-14.05***	-12.63	-3,633***	-4,849*
	(0.61)	(0.68)	(5.26)	(12.37)	(1,159)	(2,520)
Vacancy treatment (δ_{Vac})	1.05*	1.01**	11.05**	21.17***	2,048**	4,061***
	(0.57)	(0.43)	(4.40)	(6.92)	(942)	(1,499)
× high intensity (γ_{Vac})	-1.62**	-0.98	-13.40**	-13.56	-3,565***	-4,739*
	(0.80)	(0.68)	(6.39)	(12.12)	(1,356)	(2,554)
Combined treatment (δ_{Com})	0.48	0.02	5.06	2.82	1,162	837
	(0.60)	(0.47)	(5.29)	(9.16)	(1,140)	(1,759)
× high intensity (γ_{Com})	-1.23	-0.42	-9.28	-4.02	-2,963**	-2,586
	(0.82)	(0.77)	(6.90)	(13.75)	(1,457)	(2,704)
Treatment intensity regime (ref. super-control)						
Medium intensity (α_M)	-0.60	-0.50	-3.96	-8.88	30	377
	(1.05)	(0.80)	(8.06)	(11.72)	(1,414)	(2,048)
High intensity (α_H)	0.93	0.58	4.44	2.76	2,061	3,182
	(1.02)	(0.89)	(7.98)	(14.15)	(1,369)	(2,235)
P-value: differential treatment effects						
$\delta_{\text{Rec}} = \delta_{\text{Vac}}$	0.934	0.154	0.848	0.108	0.796	0.446
$\delta_{\text{Rec}} = \delta_{\text{Com}}$	0.291	0.577	0.351	0.673	0.337	0.463
$\delta_{\text{Vac}} = \delta_{\text{Com}}$	0.264	0.055	0.173	0.054	0.377	0.090
P-value: differential treatment spillovers						
$\gamma_{\text{Rec}} = \gamma_{\text{Vac}}$	0.626	0.998	0.917	0.934	0.962	0.964
$\gamma_{\text{Rec}} = \gamma_{\text{Com}}$	0.320	0.427	0.457	0.506	0.661	0.429
$\gamma_{\text{Vac}} = \gamma_{\text{Com}}$	0.578	0.403	0.486	0.428	0.628	0.367
No. of observations	92,098	92,098	92,098	92,098	92,098	92,098
Mean dep. variable (super-control)	41.67	47.00	338.2	787.5	62,116	145,013
Control variables						
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Market-strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports the results of interacted regressions of treatment indicators and local treatment intensity regimes as described by 4 estimated for the full experimental population. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level.

correspond to relative increases of 2.6% in employment rates, 3.0% in working hours, and 3.8% in earnings relative to the super-control group. The initial positive impact of the recommendation treatment attenuates over time. After 12 months, differences in employment rates and working hours are no longer statistically significant, while the earnings effect remains significant at the 10% level.

Job seekers assigned to the *vacancy treatment* in medium-intensity regions also experience higher employment rates, working hours, and earnings, with effects that are more persistent than for the recommendation treatment. After 12 months, job seekers in the vacancy treatment exhibit a 1.0 percentage-point higher monthly employment rate ($p = 0.021$), work approximately 21.2 additional hours ($p = 0.003$), and earn DKK 4,061 more ($p = 0.008$) than those in the control group, corresponding to relative increases of 2.1%, 2.7%, and 2.8%, respectively.

By contrast, we find no statistically significant effects of the *combined treatment*, which provides both vacancy information and occupational recommendations. This suggests that different forms of advice, on average, offset rather than complement each other in our setting. While differences between the combined treatment and the other treatment arms are generally not statistically significant, outcomes for job seekers in the combined treatment after twelve months are weakly lower than those in the vacancy treatment, with p-values of 0.055 for employment, 0.054 for working hours, and 0.090 for earnings.

Finally, the negative interaction coefficients γ_{Rec} and γ_{Vac} indicate that higher treatment intensities significantly reduce employment rates, working hours, and labor earnings for job seekers receiving occupational recommendations or vacancy information. This finding reinforces our earlier evidence that negative treatment spillovers among treated job seekers can reduce, or even fully offset, the positive effects of advice at high treatment intensities.

5.1 Which occupations do job seekers target?

In a next step, we examine treatment-specific shifts in job search behavior among job seekers receiving occupational recommendations, vacancy information, or both. To this end, we again use data on registered job applications, which include an identifier for the occupation associated with each application (see Section 2.3). This enables us to distinguish between applications to (1) a job seeker's *core occupations*, defined as all occupations stored in the individual's personal job search profile at the onset of the intervention, and (2) *recommended occupations*, defined as all occupations that our algorithm recommends (or would recommend) for a given job search profile. Based on this distinction, we analyze the share of job applications directed toward core and recommended occupations within one month and twelve months following the start of the experiment.[13] In addition, we examine the average labor market tightness of the occupations applied to, measured in the week prior to the experiment.

Several features of the data may limit the statistical power of this analysis. First, job seekers register applications only while unemployed, and some may not register any applications at all. Second, registered applications capture only a subset of all applications, as job seekers are required to register only two applications per week. For these reasons, our baseline analysis in Table 6 focuses on treatment differences in application behavior without conditioning on local treatment intensity.[14]

As a complementary outcome capturing treatment-specific differences in occupational search, we examine the occupations of realized job matches. Specifically, we estimate treatment effects on employment rates, working hours, and earnings separately for matches in job seekers' core occupations and the occupations recommended by our algorithm. To limit the influence of treatment spillovers, the analysis in Figure 3 focuses on regions assigned to the medium-intensity regime.

Recommendation treatment: Job seekers respond to occupational recommendations by adjusting their search behavior. Relative to the control group, individuals in the recommendation treatment send a larger share of their applications to recommended occupations within the first month (+2.3%; $p = 0.041$; see column 3 of Table 6), while reducing the share of applications sent to their core occupations (-1.5%; $p = 0.018$; see column 1). In addition, the estimates in column (5) indicate that treated individuals concentrate their search on occupations characterized by higher labor market tightness at the onset of the experiment. On average, job seekers in the recommendation treatment

[13] In the *joblog* system, job seekers may register applications to both core and non-core occupations. Empirically, we observe that approximately 53% of applications are directed to core occupations stored in job seekers' personal job search profile.

[14] This approach implicitly assumes that job seekers' allocation of search effort is not affected by spillover effects. Appendix Table A.2 reports results from interacted specifications that explicitly allow for such spillovers. While these estimates provide no evidence that job seekers adjust their search behavior in response to local treatment intensity, we acknowledge that this analysis may be underpowered. Accordingly, our discussion of search behavior focuses on the one-month horizon, where spillover concerns are less pronounced. Consistent with this, Table 6 shows that treatment differences attenuate when extending the horizon from one to twelve months.

apply to occupations with 5.7% more vacancies per job seeker compared to the control group ($p = 0.004$).

Table 6: Treatment differences in registered job applications

Dependent variable	Fraction core occupations (in %-points)		Fraction recom. occupations (in %-points)		Avg. labor market tightness$^{(a)}$	
	1m. (1)	12m. (2)	1m. (3)	12m. (4)	1m. (5)	12m. (6)
Treatment status (ref. control group)						
Recommendation treatment (δ_{Rec})	-0.77**	-0.55**	0.60**	0.29	0.77**	0.44
	(0.32)	(0.27)	(0.29)	(0.25)	(0.37)	(0.35)
Vacancy treatment (δ_{Vac})	0.91***	0.46*	-0.13	-0.29	0.68*	0.40
	(0.32)	(0.27)	(0.29)	(0.25)	(0.37)	(0.35)
Combined treatment (δ_{Com})	0.60*	0.35	0.42	0.19	0.68*	0.48
	(0.32)	(0.27)	(0.29)	(0.25)	(0.37)	(0.35)
P-value: differential treatment effects						
$\delta_{\text{Rec}} = \delta_{\text{Vac}}$	0.000	0.001	0.021	0.036	0.816	0.928
$\delta_{\text{Rec}} = \delta_{\text{Com}}$	0.000	0.003	0.561	0.720	0.822	0.916
$\delta_{\text{Vac}} = \delta_{\text{Com}}$	0.373	0.710	0.087	0.082	0.994	0.845
No. of observations	82,957	87,937	82,957	87,937	82,957	87,937
Mean dep. variable (control group)	52.6	51.2	26.5	26.8	13.5	16.3
Control variables						
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Market-strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports treatment differences in registered job applications relative to the control group. The sample includes job seekers who register any job application within the corresponding observation period. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level.
$^{(a)}$Refers to the average number of posted vacancies per 100 job seekers (measured based on posted vacancies on the online platform and search profiles in the week prior to the experiment) within the occupations applied to over one month and twelve months following the start of the experiment, respectively.

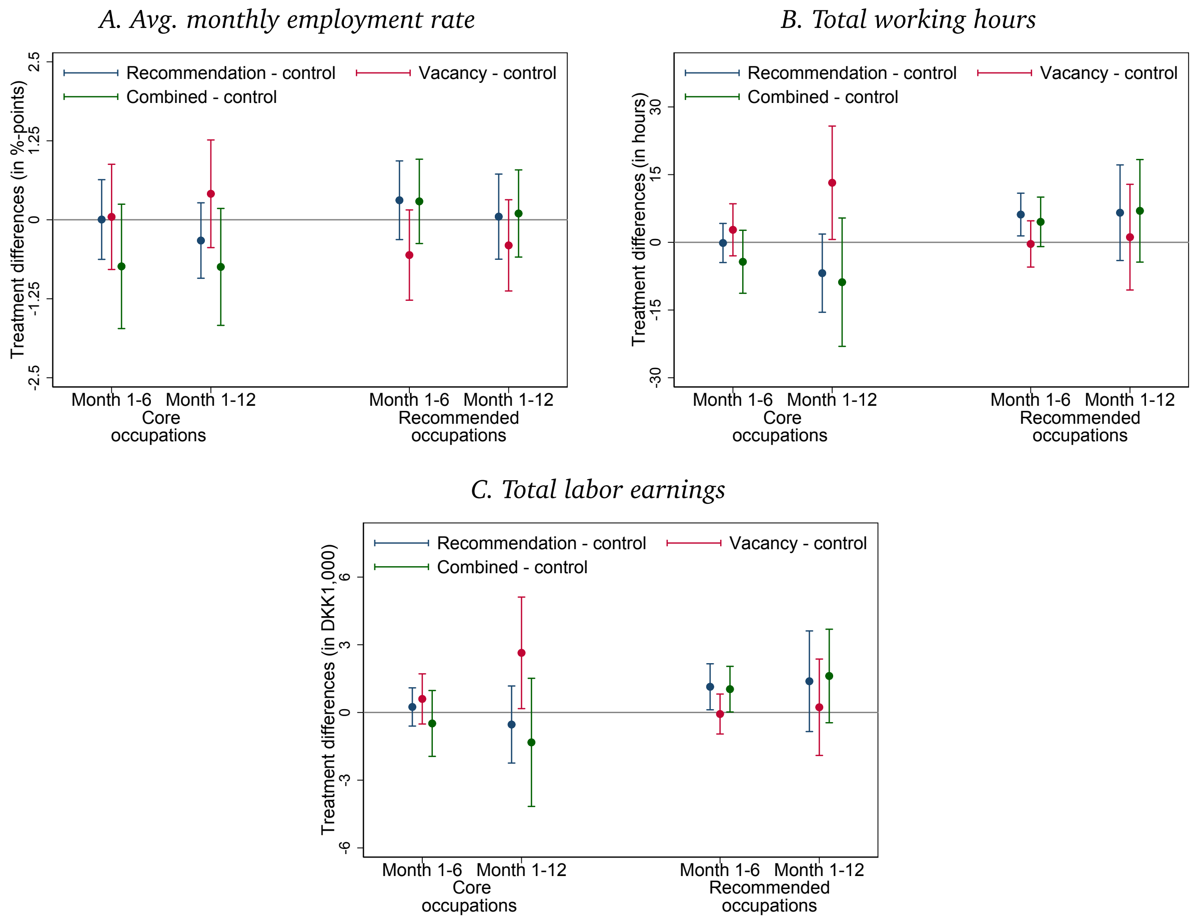
These effects are consistent with the idea that occupational recommendations convey information about skill alignment, thereby increasing job seekers' perceived returns to searching in the recommended occupations and encouraging them to redirect search effort accordingly. In line with this interpretation, the blue point estimates in Figure 3 show that the recommendation treatment leads to higher working hours (+4.9%; $p = 0.038$) and higher earnings (+4.9%; $p = 0.073$) in recommended occupations over a six-month horizon. These gains account for roughly 55% of the corresponding increases in total working hours and earnings reported in Table 5. While this indicates that a substantial share of the overall treatment effect operates through employment in recommended occupations, the remaining gains—and the absence of effects in core occupations—suggest that occupational recommendations also induce job seekers to expand their search to other non-core occupations beyond those explicitly recommended.

Vacancy treatment: In contrast to occupational recommendations, the vacancy treatment increases, on average, the share of applications sent to job seekers' core occupations (+1.7%; $p = 0.005$; see column 1). This shift is accompanied by an increase in the average labor market tightness within the occupations to which job seekers apply (+5.0%; $p = 0.069$), resembling the corresponding effect of the recommendation treatment. Interpreted through the lens of our theoretical framework, these patterns suggests that, on average, job seekers perceive vacancy information as a positive signal regarding the returns to searching within their core occupations. For instance, many treated individuals may be positively surprised by the number of available vacancies in their core occupations and update their beliefs about job prospects in these fields.

This interpretation is further supported by the red point estimates in Figure 3, which show that the vacancy treatment increases cumulative working hours (+3.9%; $p = 0.091$) and earnings (+4.1%; $p = 0.086$) in core occupations over a one-year horizon. These gains account for 62% and 65% of the corresponding increases in total working hours and earnings (see Table 5). At the same time, the effects of vacancy information likely depend on whether job seekers receive favorable or unfavorable signals about labor market tightness in their core occupations. We examine this heterogeneity in Section 5.2, where we analyze treatment effects by the initial tightness of job seekers' core occupations.

Note that, for both the recommendation and vacancy treatments, effects on registered applications are smaller than the corresponding effects on realized employment and earnings. This pattern is consistent with the fact that the applications data capture only a subset of job seekers' search behavior and do not reflect changes in overall search intensity. In addition, the treatments may help job seekers to target their search towards the most promising options *within* the set of core or recommended occupations, which is in line with our finding that treated job seekers apply to occupations with higher labor market tightness than those in the control group.

Figure 3: Occupations of realized job matches



Note: The figure shows treatment differences (with 90% confidence intervals) in labor market outcomes accumulated across different occupations during the six and 12 months following the start of the experiment. We compare each advice type with the control group, restricting the sample to job seekers in municipalities assigned to the medium-intensity regime. All specifications include individual controls and market-strata fixed effects, and standard errors are clustered at the municipality level. For each outcome (employment, working hours, and earnings), we distinguish between a job seeker's *core occupations*—the ones stored in the search profile at the start of the intervention—and *recommended occupations*—the ones that were or would have been recommended based on the personal job search profile at the beginning of the intervention.

Combined treatment: When examining the application behavior of job seekers in the combined treatment, we find that treated individuals send a somewhat larger share of applications to their core occupations (+1.1%; $p = 0.064$), with the increase being somewhat less pronounced than the corresponding effect in the vacancy treatment. At the same time, we observe a small and statistically insignificant increase in the share of applications sent to recommended occupations. In addition, individuals in the combined treatment apply to occupations with a labor market tightness that is 5.0% higher ($p = 0.069$) than in the control group. Taken together with the findings from Table 5 and Figure 3 (green point estimates), these patterns indicate that combining occupational recommendations with vacancy information does not translate into additional gains in employment or earnings. One possible interpretation is that the two types of advice are perceived as conflicting signals, partially offsetting each other when being combined. An alternative interpretation is that providing multiple types of advice simultaneously may lead to information overload for job seekers with limited attention, reducing the effectiveness of either signal.

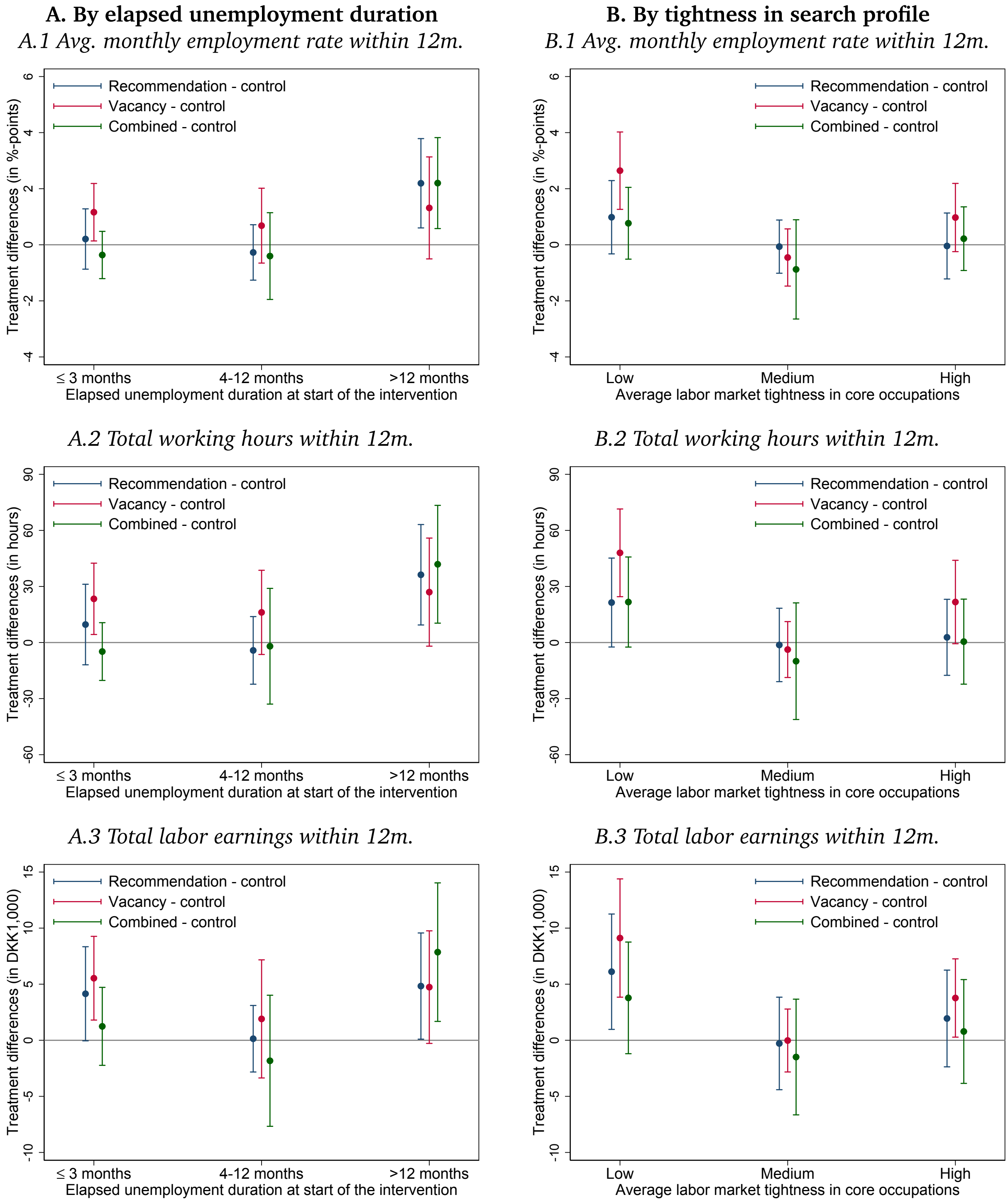
5.2 Who benefits from advice?

Since advice improves labor market outcomes at moderate treatment intensities but loses effectiveness at higher intensities, it may be beneficial to limit its provision to a subset of unemployed individuals. With this in mind, we examine heterogeneous treatment effects, focusing on individuals in regions assigned to the medium-intensity regime, where treatment spillovers play a more limited role. Specifically, we analyze differential treatment effects along two dimensions: (1) job seekers' unemployment duration at the start of the intervention and (2) the labor market tightness in job seekers' core occupations. We note that these estimates are naturally less precise, as the heterogeneity analysis partitions the sample into multiple subgroups within each treatment arm.

Heterogeneity by unemployment duration: Panel A of Figure 4 shows that occupational recommendations are particularly effective for individuals who have been unemployed for twelve months or longer. For this group, the recommendation treatment significantly increases employment rates, working hours, and earnings by 4–7% over a twelve-month horizon, while we find no significant effects for job seekers with shorter unemployment durations. This pattern is in line with previous evidence by Belot *et al.* (2019), who argue that long-term unemployed individuals might be more responsive to occupational referrals as their past search strategies have yielded limited success. Notably, for this group, the combined treatment also leads to significant improvements in employment, working hours, and earnings of a similar magnitude. By contrast, the vacancy treatment has similar employment and earnings effects for job seekers at different stages of their unemployment spell.[15]

[15]The effects of the combined treatment on employment rates differ significantly between long-term and short-term unemployed ($p = 0.011$) and between long-term and medium-term unemployed ($p = 0.051$). Likewise, the recommendation treatment has a significantly different impact on long-term unemployed

Figure 4: Heterogeneous effects of search advice



Note: The figure shows treatment differences (with 90% confidence intervals) in labor market outcomes during the 12 months following the start of the experiment for different subgroups. We compare each advice type with the control group, restricting the sample to job seekers in municipalities assigned to the medium-intensity regime. All specifications include individual controls and market-strata fixed effects, and standard errors are clustered at the municipality level.

compared to short-term ($p = 0.091$) and medium-term unemployed ($p = 0.030$). In contrast, we cannot reject the null hypothesis that the effects of the vacancy treatment are equal across the three groups.

Heterogeneity by labor market tightness: Panel B of Figure 4 illustrates that occupational recommendations and vacancy information tend to be particularly effective for job seekers facing unfavorable labor market conditions. Among individuals in the lowest tercile of the occupational tightness distribution, both the recommendation and vacancy treatments are associated with improvements in labor market outcomes. This pattern is consistent with our earlier finding that advice shifts job seekers toward occupations with higher labor market tightness, thereby benefiting individuals who were initially targeting occupations with relatively few vacancies (cf. Table 6). Point estimates for the combined treatment are also positive in the lowest tightness tercile, though they are not statistically significant at conventional levels. For job seekers targeting occupations with intermediate levels of tightness, we do not find significant treatment effects for any type of advice. Notably, in the highest tightness tercile, estimates for the vacancy treatment are positive across all outcomes, although only the effect on earnings is statistically significant. We find no corresponding effects for the recommendation or combined treatments.[16]

The finding that the vacancy treatment is effective for job seekers initially searching in low-tightness occupations may at first seem at odds with the earlier evidence that, on average, this treatment leads job seekers to apply to and find employment in their core occupations (Table 6 and Figure 3). The finding is, however, consistent with the theoretical idea that vacancy information can be informative both when it conveys strongly negative and strongly positive signals about labor market conditions in core occupations (Section 3). To examine this idea more directly, we analyze realized job matches—distinguishing between core and non-core occupations—while splitting the sample by the tightness of job seekers' core occupations. As shown in Appendix Table A.3, the vacancy treatment indeed induces different occupational shifts depending on initial labor market conditions. For job seekers initially searching in low-tightness occupations—who may plausibly interpret the vacancy information as a negative signal about conditions in their core occupations—the treatment significantly increases employment, working hours, and earnings in other, *non-core* occupations (see column (2) of Table A.3). By contrast, for job seekers initially searching in medium- or high-tightness

[16]When comparing differential treatment effects across subgroups, we find that the effect of the vacancy treatment on earnings differs significantly between job seekers in labor markets with low and medium tightness levels ($p = 0.003$). For all other pairwise comparisons, we cannot reject the null hypothesis that treatment effects are constant across different levels of market tightness.

occupations—where vacancy information provides a more favorable signal—the effects of the vacancy treatment tend to be concentrated in core occupations (see columns (3) and (5) of Table A.3).

5.3 Do different types of advice generate distinct externalities?

In the final part of our analysis, we turn to the question of whether different types of advice generate distinct spillovers on other job seekers. While our experiment is not designed to separately identify the spillover effects of different forms of advice—since we do not independently vary the regional shares of job seekers in the different treatment arms—our data nonetheless allow us to provide some suggestive evidence on this question. We do so by exploiting natural variation in how job seekers searched across occupations and regions in the pre-intervention period. As detailed in Appendix B.4, we use this variation to construct two separate measures of individual-level exposure to other job seekers receiving different forms of advice—one capturing exposure to vacancy information and one capturing exposure to occupational recommendations—and compare outcomes of treated and untreated job seekers across high- and low-exposure markets for each type of advice.

The results reported in Appendix Table B.2 reveal three patterns that are broadly consistent with our earlier findings. First, advice significantly increases employment and earnings for treated job seekers in markets with low exposure to both types of advice. Second, these gains diminish when many job seekers receive occupational recommendations (either through the recommendation or the combined treatment), consistent with congestion effects when more individuals are steered toward similar alternative occupations. By contrast, high exposure to other job seekers receiving vacancy information does not attenuate treatment effects among treated job seekers. Third, negative spillovers on the control group tend to arise in markets with high exposure to vacancy information, consistent the observation that job seekers receiving vacancy information, on average, concentrate their search in core occupations, thereby increasing competition for non-treated individuals. Conversely, untreated job seekers experience small (though imprecisely estimated) positive effects in markets with high exposure to occupational recommendations, where congestion in their core occupations may be alleviated.

6 Conclusion

This paper studies the direct and indirect effects of online job search advice using a large-scale field experiment embedded in the the official online platform of the Danish public employment service. By varying the content of advice and the share of job seekers receiving advice across local labor markets, we provide evidence on both the individual-level benefits of online job search advice and its spillovers on other treated and untreated job seekers.

Our results yield three main conclusions. First, online job search advice can meaningfully improve employment and earnings when provided to a limited share of job seekers. Second, the positive effects of advice decline when more job seekers receive advice. We show that negative spillovers among treated job seekers can fully offset the positive effects of advice at high treatment intensities. Spillovers on untreated job seekers are heterogeneous and depend on how the intervention reshapes occupational competition and on the initial distribution of labor market tightness. Third, both occupational recommendations and vacancy information positively impact employment and earnings at intermediate levels of treatment intensity. These effects are accompanied by systematic changes in job search behavior: occupational recommendations lead job seekers to apply more to, and find employment in, recommended occupations, whereas vacancy information, on average, leads job seekers to concentrate on their core occupations. Moreover, combining vacancy information with occupational recommendations produces weaker employment and earnings effects than providing either form of advice individually. This suggests that different types of advice may partially offset each other's effectiveness, for instance, by providing conflicting signals about which occupations to target or by generating information overload when multiple personalized signals are delivered simultaneously.

A number of caveats are worth noting. While much of our evidence points to a reallocation of search effort across occupations as a key mechanism, we cannot rule out that advice also increases job seekers' overall search intensity. In addition, we do not observe job seekers' beliefs about employment prospects across occupations, which would be valuable for isolating the mechanisms through which different types of advice shape labor market outcomes. Finally, our design does not allow us to precisely estimate differential spillovers of different types of advice, although our data provide preliminary insights into their likely direction.

Despite these limitations, our findings have clear implications for policy and future research. They underscore that the effectiveness of online job search advice critically depends on scale, providing a cautionary tale that interventions that have proven successful in smaller trials might be difficult to roll out to the full population (see also Al-Ubaydli *et al.*, 2017, 2019; Muralidharan and Niehaus, 2017). Our results, together with complementary evidence by Belot *et al.* (2025a) and Belot *et al.* (2025b), suggest that it might be promising to target advice to specific groups, such as the long-term unemployed or individuals searching in slack labor markets. An alternative, complementary approach might be to mitigate congestion effects by designing recommender systems that explicitly account for equilibrium considerations, as pioneered by Naya *et al.* (2023) and Behaghel *et al.* (2024).

More broadly, our results highlight the need for further research on the interdependencies between different types of advice, and between online advice and other aspects of the job search process, such as additional features of online job boards, or advice from caseworkers. As public employment services and private platforms increasingly rely on algorithmic recommendations and real-time information, understanding how different tools interact and how job seekers process multiple signals will be central to designing effective and scalable labor market policies.

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Online Appendix

The Direct and Indirect Effects of Online Job Search Advice

Steffen Altmann **Anita M. Glenny**
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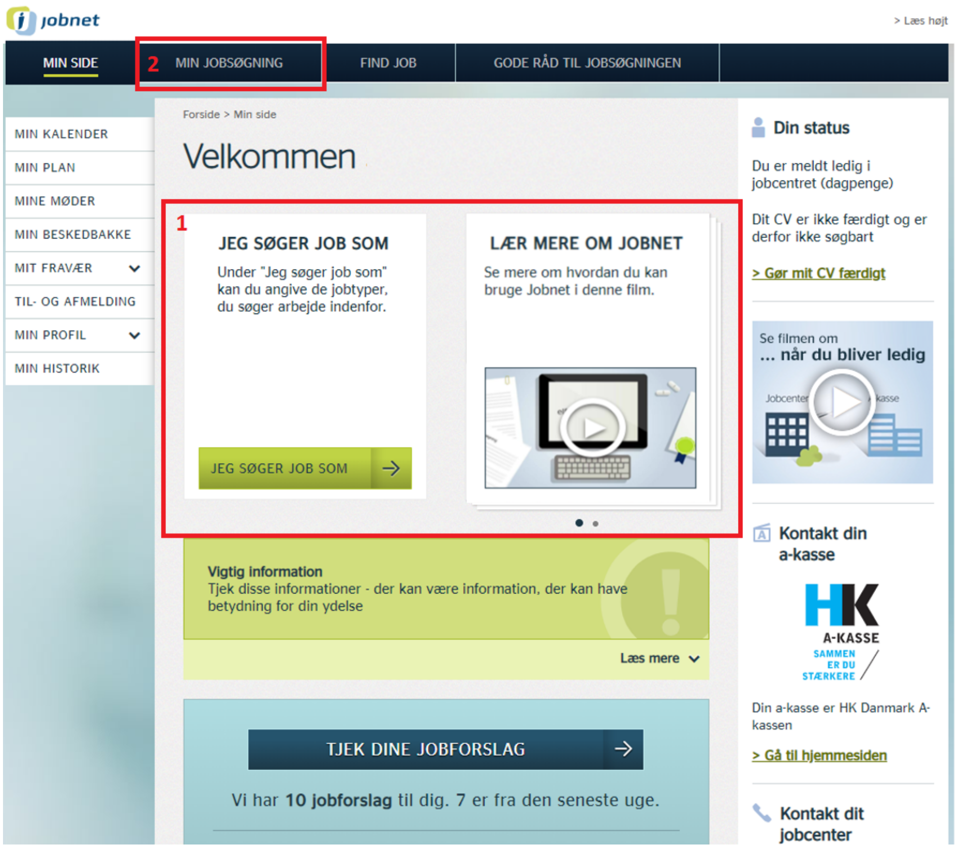
A Additional Figures and Tables

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

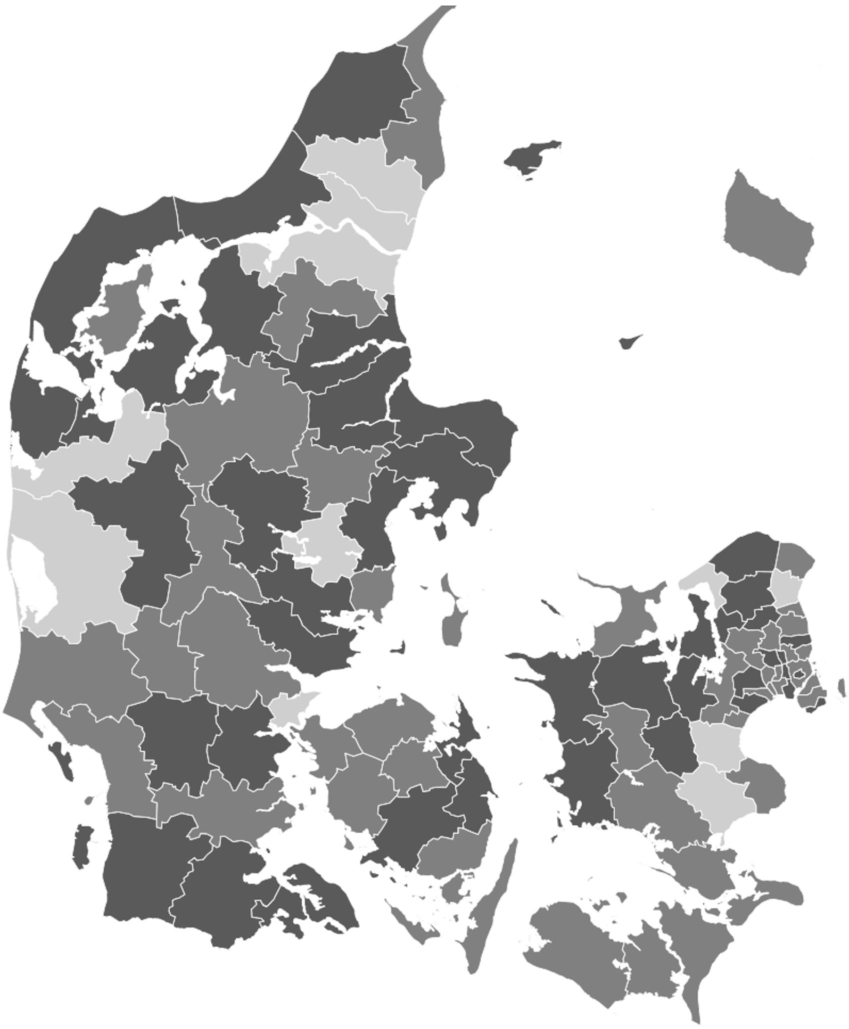


Note: The figure shows a screenshot of the landing page of the Danish employment agency's online portal, *jobnet.dk*. The red box labeled (1) highlights the dashboard, while the tab labeled (2) directs job seekers to their personal profile, where they can store preferred occupations and register their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

Figure A.2: Content of online dashboard

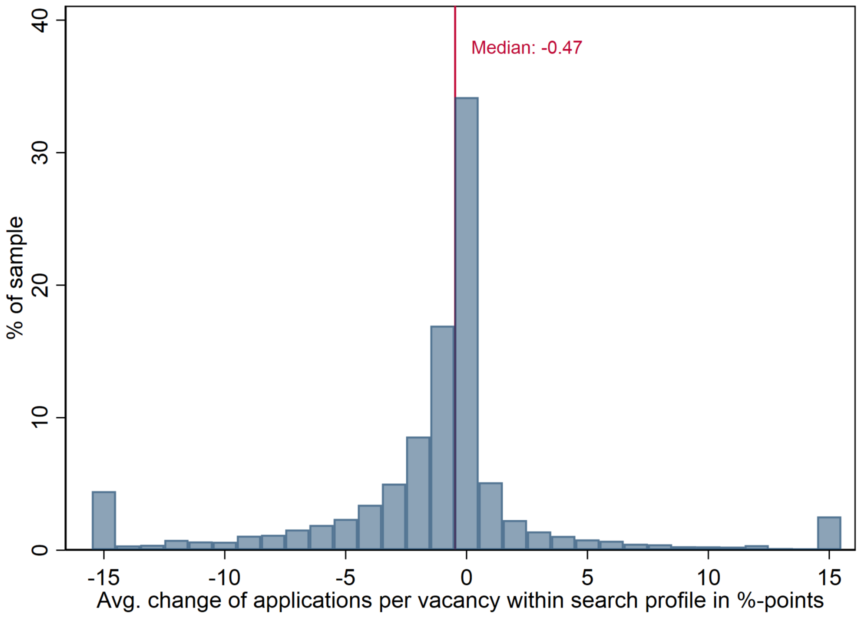
The figure illustrates the different information cards displayed on the dashboard in our experiment. English translations of the Danish text on these cards are as follows: **Panel A:** You are searching for a job as a “canteen manager”. The following occupations may also be relevant for you: chef de cuisine, kitchen staff, and chef. **Panel B:** Within your local area, there are currently 37 vacancies in the occupations you are searching for. **Panel C:** Under “I am looking for a job as”, you can specify the types of jobs you are searching for. **Panel D:** Learn more about how you can use Jobnet in this video.

Figure A.3: Geographical distribution of treatment regimes



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

Figure A.4: Changes of competition in core occupations



Note: The figure illustrates the distribution of a variable representing the change of competition within job seekers' core occupations (averagin across all core occupations of individual job seekers). This variable is derived from the number of applications submitted by treated individuals to the respective occupations during the post- and pre-intervention periods (a three-month window before and after the start of the intervention).

Table A.1: Summary statistics and balance tests

	Mean values by treatment status and intensity regime					
	Control group			Treatment group		Balance stat.
	Super-control	Medium-intensity	High-intensity	Medium-intensity	High-intensity	$P-$value
No. of observations	10,100	18,150	3,716	27,082	33,050	
Male	48.3	47.0	47.1	46.8	47.1	0.813
Age group						
18-25 years	13.3	10.4	10.6	10.1	11.9	0.060
26-35 years	32.6	34.3	32.9	34.5	32.5	0.890
36-45 years	17.8	19.8	17.6	19.5	18.6	0.211
46-55 years	19.0	19.2	19.8	19.0	18.9	0.566
56-65 years	17.3	16.3	19.1	16.8	18.1	0.224
Married	55.9	56.4	52.9	56.0	54.1	0.612
Any children	37.1	35.8	38.4	35.9	38.5	0.960
Danish citizen	81.5	75.1	78.3	75.2	78.1	0.068
Level of education						
Lower secondary education	20.6	18.1	19.2	18.1	19.9	0.733
Upper secondary education	43.7	39.4	44.8	39.7	43.7	0.402
Bachelor's degree or equiv.	25.6	27.6	24.9	27.4	24.9	0.945
Master's degree or equiv.	7.3	11.5	8.6	11.4	8.7	0.490
Elapsed unemployment duration						
<1 month	14.8	14.6	14.9	14.2	14.4	0.644
1–3 months	28.8	28.4	30.4	29.0	29.7	0.065
4–6 months	21.1	21.9	21.1	21.6	22.3	0.200
7–12 months	22.5	22.2	21.4	22.1	21.4	0.876
13–24 months	11.6	11.8	11.2	12.0	11.1	0.688
>24 months	1.1	1.1	1.0	1.1	1.0	0.946
Outcomes in previous year						
Earnings in DKK1,000	18.0	18.4	18.7	18.5	18.6	0.867
Working hours	989	972	999	981	1,004	0.741
Previous occupation						
Managerial position	1.9	2.0	1.9	2.0	1.9	0.975
Professional position	13.1	16.4	15.0	16.2	14.4	0.247
Technical or assoc. position	6.0	6.4	6.9	6.2	6.3	0.615
Clerical support worker	8.6	9.4	9.2	10.3	9.0	0.100
Service sales worker	20.3	20.1	19.4	20.1	19.9	0.953
Agricultural worker	0.6	0.6	0.8	0.6	0.7	0.848
Craft worker	6.8	5.1	5.3	5.1	5.8	0.378
Plant machine operator	5.4	4.2	5.9	4.2	5.9	0.671
Elementary occupation	15.7	15.1	15.6	14.5	15.5	0.438
Labor market tightness[(a)]	6.7	8.3	7.9	8.2	8.2	0.615

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

[(a)]Labor market tightness is calculated as the average number of posted vacancies in a given occupation per 100 job seekers who included that occupation in their search profile at the start of the intervention. For each job seeker, we compute the average tightness across all occupations in their search profile.

Table A.2: Job search behavior: direct and indirect effects on registered job applications

Dependent variable	Fraction core occupations (in %-points)		Fraction recom. occupations (in %-points)		Avg. labor market tightness[(a)]	
	1m. (1)	12m. (2)	1m. (3)	12m. (4)	1m. (5)	12m. (6)
Recommendation treatment (δ_{Rec})	-0.83**	-0.68**	0.32	0.22	0.86	0.46
	(0.41)	(0.31)	(0.54)	(0.36)	(0.66)	(0.55)
$\times$ high intensity γ_{Rec}	-0.01	-0.27	0.45	0.20	-0.46	-0.75
	(0.78)	(0.64)	(0.90)	(0.70)	(0.90)	(0.80)
Vacancy treatment (δ_{Vac})	0.75***	0.08	-0.47	-1.01***	0.79	0.73
	(0.28)	(0.24)	(0.41)	(0.34)	(0.55)	(0.56)
$\times$ high intensity γ_{Vac}	0.13	0.17	0.21	0.88	0.56	-0.43
	(0.75)	(0.62)	(0.85)	(0.74)	(0.81)	(0.77)
Combined treatment (δ_{Com})	0.64*	0.60**	0.80	0.43	0.82	0.21
	(0.36)	(0.30)	(0.50)	(0.40)	(0.52)	(0.40)
$\times$ high intensity γ_{Com}	0.06	-0.57	-0.75	-0.25	-0.70	-0.33
	(0.73)	(0.62)	(0.86)	(0.71)	(0.76)	(0.67)
Treatment intensity regime (ref. super-control)						
Medium intensity (α_M)	-1.64**	-1.15	-0.24	-0.28	0.14	0.41
	(0.76)	(0.82)	(1.68)	(1.64)	(1.10)	(1.54)
High intensity (α_H)	-0.47	0.27	-0.96	-1.36	0.49	0.56
	(0.92)	(0.91)	(1.69)	(1.63)	(1.18)	(1.71)
P-value: differential treatment effects						
$\delta_{\text{Rec}} = \delta_{\text{Vac}}$	0.000	0.025	0.327	0.017	0.289	0.441
$\delta_{\text{Rec}} = \delta_{\text{Com}}$	0.004	0.002	0.516	0.685	0.942	0.605
$\delta_{\text{Vac}} = \delta_{\text{Com}}$	0.810	0.170	0.009	0.001	0.195	0.733
P-value: differential effects treatment spillovers						
$\gamma_{\text{Rec}} = \gamma_{\text{Vac}}$	0.818	0.406	0.789	0.287	0.244	0.629
$\gamma_{\text{Rec}} = \gamma_{\text{Com}}$	0.919	0.575	0.171	0.483	0.703	0.520
$\gamma_{\text{Vac}} = \gamma_{\text{Com}}$	0.901	0.163	0.132	0.030	0.063	0.855
No. of observations	82,957	87,937	82,957	87,937	82,957	87,937
Mean dep. variable (super-control)	61.9	60.6	32.8	33.9	12.2	15.4
Control variables						
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Market-strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports the results of interacted regressions of treatment indicators and local treatment intensity regimes estimated for the full experimental population. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level.

[(a)]Refers to the average number of posted vacancies per 100 job seekers (measured based on posted vacancies on the online platform and search profiles in the week prior to the experiment) within the occupations applied to over one month and twelve months following the start of the experiment, respectively.

Table A.3: Effect of vacancy treatment on realized occupations by labor market tightness

	Labor market tightness in core occupations					
	Low		Medium		High	
	Core occupations (1)	Non-core occupations (2)	Core occupations (3)	Non-core occupations (4)	Core occupations (5)	Non-core occupations (6)
A. Dependent variable: avg. monthly employment rate within 12 months by occupation						
Treatment status (ref. control group)						
Vacancy treatment	0.23	2.44***	0.27	-0.70	0.57	0.31
	(0.78)	(0.75)	(0.87)	(0.69)	(0.64)	(0.76)
Mean (control group)	20.91	23.42	23.06	21.75	28.07	19.68
B. Dependent variable: working hours within 12 months by occupation						
Treatment status (ref. control group)						
Vacancy treatment	11.91	28.06**	9.38	-11.41	15.41	6.43
	(11.51)	(11.61)	(11.34)	(10.90)	(10.41)	(10.04)
Mean (control group)	292.2	363.3	318.2	347.7	403.9	333.5
C. Dependent variable: labor earnings in DKK within 12 months by occupation						
Treatment status (ref. control group)						
Vacancy treatment	2,139	5,389**	1,816	-1,503	3,274*	528
	(2,503)	(2,210)	(2,012)	(1,956)	(1,928)	(1,691)
Mean (control group)	59,033	69,879	57,324	63,456	76,682	65,211
No. of observations	8,330	8,330	9,758	9,758	9,226	9,226
Control variables						
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Market-strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports results from regressions of labor market outcomes on treatment status (vacancy treatment vs. control) for individuals in the medium-intensity regime. We distinguish between outcomes in job seekers' core occupations (columns 1, 3 and 5)—those listed in their search profile at the start of the intervention—and in non-core occupations (columns 2, 4 and 6), defined as all remaining occupations. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level.

B Additional Evidence on Treatment Spillovers

In this section, we present additional evidence on treatment spillovers using several alternative definitions of local labor markets. Since job seekers may search beyond their own municipality, we use the experimental variation in treatment assignment at the municipality level to construct continuous treatment-intensity measures that account for geographical mobility. We first describe the construction of these alternative intensity measures, then present descriptive evidence on their properties, and finally assess the robustness of our spillover results when using them. In addition, we outline how we identify differential spillover effects of occupational recommendations and vacancy information.

B.1 Alternative definitions of local labor markets

We define three alternative measures. First, we simply calculate the share of treated individuals within a job seeker's own municipality and all bordering municipalities. Second, 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 in a job seeker's own municipality and all other municipalities, weighted by the corresponding proportion of commuters between any pair of municipalities. Third, we use the application data to measure the share of treated individuals who applied to similar local labor markets in the two years prior to the intervention, defined based on combinations of zip code areas and 3-digit occupations. Afterwards, we calculate the weighted average of treatment intensities over an individual's (pre-intervention) application portfolio.

For each municipality of residence j, the treatment intensity TI_j is calculated as a weighted average of the ratio of treated job seekers (assigned to one of the three treatment groups), N_m^T, to the total number of job seekers in the experiment (assigned to either the control group or the treatment groups), N_m, across all municipalities $m \in \{1, ..., M\}$:

$$TI_j = \frac{1}{M} \sum_m \frac{N_m^T}{N_m} \kappa_{mj}, \tag{B.1}$$

where κ_{mj} represents the weight assigned to each municipality m in calculation of the treatment intensity for municipality j.

- In our baseline specification, κ_{mj} is equal to one if $m = j$ and zero otherwise.
- For alternative measure 1, κ_{mj} is equal to one if municipalities m and j share a common border and it is zero otherwise.
- For alternative measure 2, we derive κ_{mj} from the commuting patterns of all Danish workers among the 98 municipalities in the three years preceding our experiment. Specifically, we calculate the fraction of workers residing in municipality j who commuted to work in municipality m during that period.
- For alternative measure 3, we use a slightly adjusted formula to provide an individual-specific intensity measure. Instead of considering the 98 municipalities, we focus on local labor markets defined by combinations of zip code areas and 3-digit occupations. A local labor market to which individual i applied within the last two years is represented by $m_i \in M_i$, while N_m^T and N_m refer to the number of treated and total job seekers, respectively, who applied to the corresponding local labor market. These numbers are obtained from the registered job applications of individuals in the experimental sample during the same two-year period. Formally, this gives alternative measure 3 as follows: $TI_i = \frac{1}{M_i} \sum_m \frac{N_m^T}{N_m} \kappa_{mi}$, where κ_{mi} is equal to one if worker i applied to the corresponding local labor market in the pre-experimental period and zero otherwise.

With these three treatment intensity measures, we can examine additional regional variations in the proportion of treated individuals and assess the robustness of our findings relative to different definitions of local labor markets.

B.2 Descriptive statistics

Figure B.1 shows the resulting distributions of the alternative intensity measures (Panel A.1–C.1) and illustrates the relationship between these measures and the original assignment of municipalities into the super-control, medium-intensity, and high-intensity regimes (Panel A.2–C.2). There is significant variation in local treatment intensities, ranging from 10% to 91% for alternative intensity measure 1 (defined based on all bordering municipalities) and from 30% to 80% for alternative intensity measures 2 and 3. Moreover, there is a substantial fraction of individuals assigned to the medium- and high-intensity regimes who encounter relatively little competition from treated individuals according to the alternative treatment intensity measures. For instance, in the lowest quartile of the distribution for alternative intensity measure 1, individuals from the super-control group, the medium-intensity regime, and the high-intensity regime are almost equally represented.

The assumption underlying all of these measures is that the experimentally induced variation at the municipality level creates exogenous variation in the proportion of treated individuals across local labor markets, regardless of how these markets are defined. Although this is not immediately clear, as the definition of local labor markets could be endogenous, we provide empirical support for the validity of this assumption in Table B.1. We show that the treatment intensity measures exhibit minimal correlation with job seekers' individual characteristics (see $p-$values at bottom of Table B.1), indicating that the share of treated job seekers is exogenous.

B.3 Robustness of treatment spillovers

Figure B.2 shows the relationship between local treatment intensities and job seekers' labor market outcomes, accumulated within one year after the start of the intervention, separately for the treatment and control groups. Consistent with the results presented in Table 3, there is no evidence that the average levels of employment and earnings for the control group vary with local treatment intensities. Specifically, the estimated coefficients are insignificant for each of the nine combinations of treatment intensities and labor market outcomes (illustrated by the blue lines in Figure B.2). Moreover, as also shown in Figure 1 in the main text, the outcomes of treated individuals consistently exceed those of non-treated individuals at the lower end of the treatment-intensity distributions. At the same time, higher local treatment intensity tend to reduce the labor market integration of treated job seekers (illustrated by the red lines in Figure B.2). For example, the labor earnings of individuals assigned to one of the treatment groups decrease by DKK 1,140 when alternative treatment intensity 1 increases by 10 percentage points ($p = 0.056$), with the negative effects being even more pronounced for alternative treatment intensities 2 and 3.

B.4 Estimating differential treatment spillovers

In this section, we describe how we estimate the differential treatment spillovers induced by occupational recommendations and vacancy information.

Identification: Our experimental design does not independently vary the share of individuals receiving these two forms of advice within a region, which makes it difficult to separately identify distinct spillover effects. We therefore exploit natural pre-intervention variation in how recipients of each type of advice typically search across occupations and regions to shed light on the likely direction of these spillovers. We use all registered job applications submitted by experiment participants in the two years prior to the intervention, each of which contains information on the firm's zip-code location and the job's 3-digit ISCO occupation code. For each of these local labor markets (zip-code$\times$ occupation segment), we calculate the share of individuals who, in the experiment, received (1) occupational recommendations (recommendation or combined treatments) or (2) vacancy information (vacancy or combined treatments). Because most job seekers apply to multiple jobs across different segments, we then compute the weighted average of these segment-level intensities across an individual's full application portfolio. This procedure corresponds to the construction of alternative intensity measure 3, except that we now distinguish between exposure to occupational recommendations and vacancy information.

By basing intensities on the locations of job applications rather than individuals' places of residence, we obtain two separate, non-collinear intensity measures for the two types of advice. It is worth noting that the two treatment-intensity measures are positively correlated, as the experiment only induces variation in the overall share of treated individuals within a region. Nonetheless, there is natural variation in how job seekers who receive occupational recommendations versus vacancy information allocate their search across occupations and regions. This generates meaningful independent variation in the two measures. When comparing the two above-median indicators for (1) occupational recommendations and (2) vacancy information, we observe a moderate positive correlation of $\rho = 0.48$.

Estimation: With these separate intensity measures, we estimate interacted regressions of the following form:

$$Y_{ij} = \delta \textsc{Advice}_i + \gamma_R(\textsc{Advice}_i \times TI_j^{\text{Rec-high}}) + \gamma_V(\textsc{Advice}_i \times TI_j^{\text{Vac-high}}) + \alpha_R TI_j^{\text{Rec-high}} + \alpha_V TI_j^{\text{Vac-high}} + X_i\Pi + \varepsilon_{ij}, \tag{B.2}$$

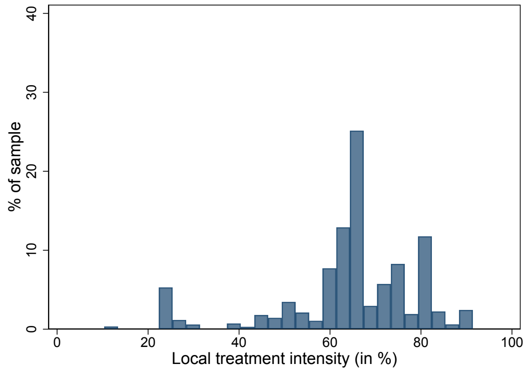
where $\textsc{Advice}_i$ indicates assignment to any of the three treatment groups, and $TI_j^{\text{Rec-high}}$ and $TI_j^{\text{Vac-high}}$ denote above-median exposure to job seekers receiving occupational recommendations and vacancy information, respectively. The coefficient δ captures treatment effects in markets with low exposure to both types of advice, while γ_R and γ_V show how these effects vary in markets with high exposure to occupational recommendations or vacancy information, respectively. α_R and α_V capture the corresponding spillovers on untreated individuals.

Results: Table B.2 reveals three patterns consistent with our main findings. First, receiving advice in markets with low exposure to any advice, significantly increases employment, working hours, and earnings. Second, these gains diminish when a large share of job seekers in the market receive occupational recommendations (negative γ_R), suggesting congestion when many individuals are directed toward the same alternative occupations. In contrast, high exposure to vacancy information does not attenuate treatment effects (near-zero γ_V). Third, negative spillovers on the control group tend to arise primarily when many job seekers receive vacancy information: earnings decline slightly and (marginally) significantly (negative α_V), consistent with the observation that job seekers receiving vacancy information, on average, concentrate their search in core occupations, thereby increasing competition for non-treated individuals. Conversely, untreated job seekers in markets with high exposure to occupational recommendations experience small (though imprecisely estimated) positive effects (positive α_R).

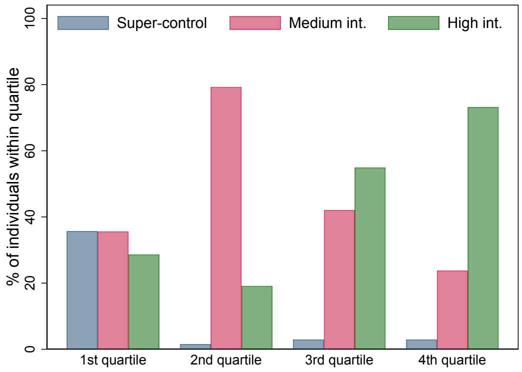
Figure B.1: Alternative treatment intensities and comparison with original assignment

A. Alternative intensity 1 – neighboring municipalities

A.1 Distribution of intensity measure

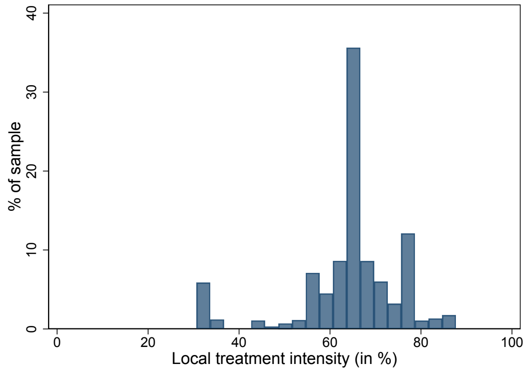


A.2 Relation to original assignment

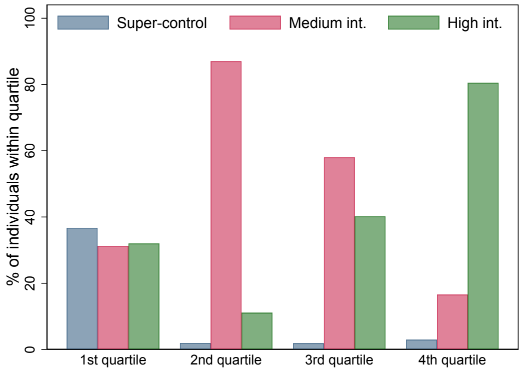


B. Alternative intensity 2 – commuting patterns

B.1 Distribution of intensity measure

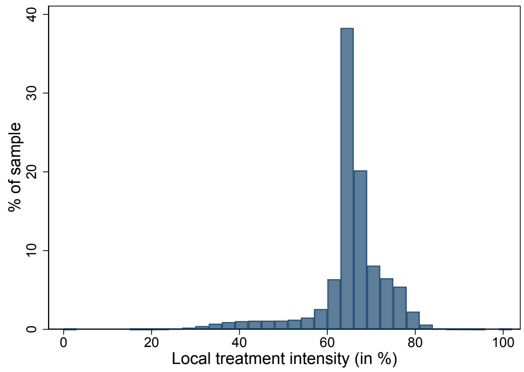


B.2 Relation to original assignment

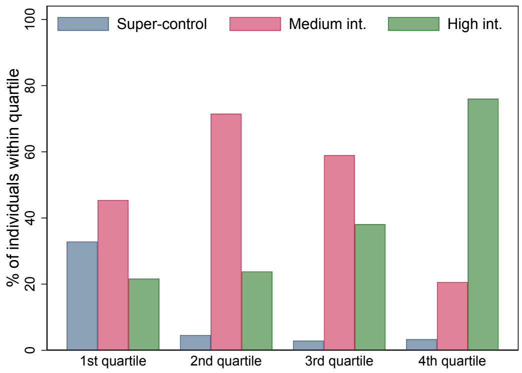


C. Alternative intensity 3 – application portfolio

C.1 Distribution of intensity measure



C.2 Relation to original assignment

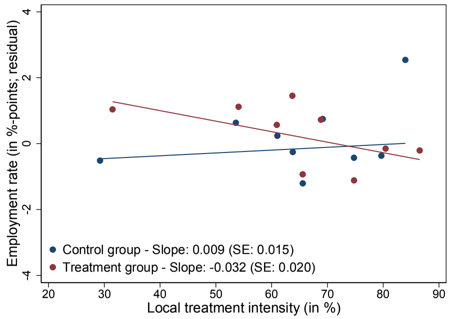


Note: The figure depicts the distribution of the local treatment intensity based on alternative definitions of local labor markets (Panel A.1–C.1) and the share of individuals from each of the three original intensity regimes (super-control, medium- and high-intensity) within quartiles of the alternative intensity distributions (Panel A.2–C.2). The alternative treatment intensity measures are defined as follows:
Alternative intensity 1: defined based on share of treated within a job seeker's own municipality and all bordering municipalities.
Alternative intensity 2: defined based on 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 (in all three treatment groups) in all other municipalities, weighted by the corresponding proportion of commuters between any pair of municipalities.
Alternative intensity 3: defined based on the share of treated individuals who applied to similar vacancies in the past. 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 individuals that applied to any given combination of zip code areas and occupations (3-digits). Afterwards, we calculate the weighted average of treatment intensities over an individual's application portfolio.

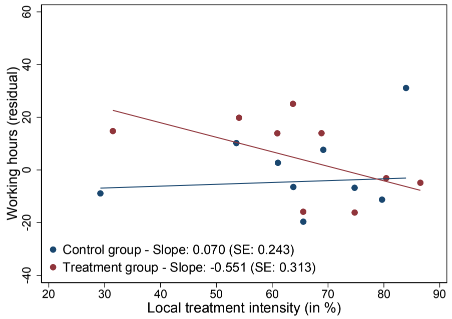
Figure B.2: Relationship between local treatment intensity and labor market outcomes

A. Alternative intensity 1 – neighboring municipalities

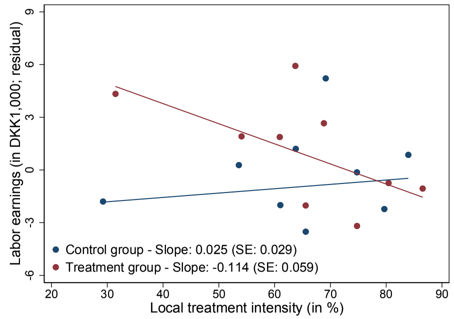
A.1 Avg. employment rate within 12m.



A.2 Total working hours within 12m.

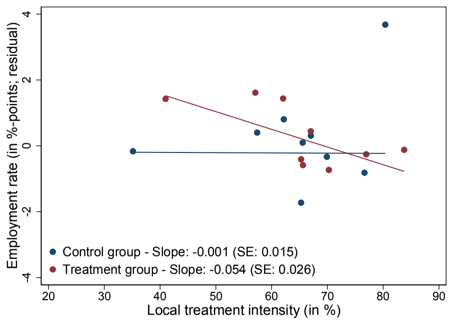


A.3 Total labor earnings within 12m.

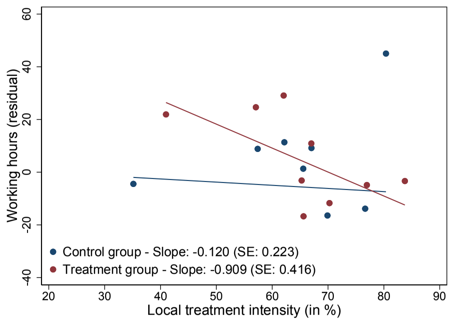


B. Alternative intensity 2 – commuting patterns

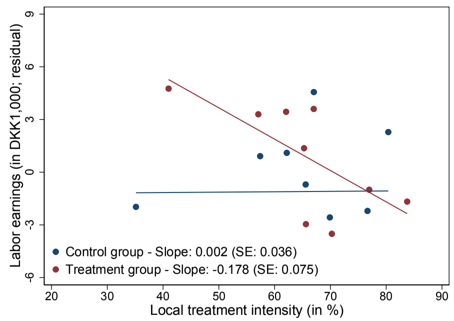
B.1 Avg. employment rate within 12m.



B.2 Total working hours within 12m.

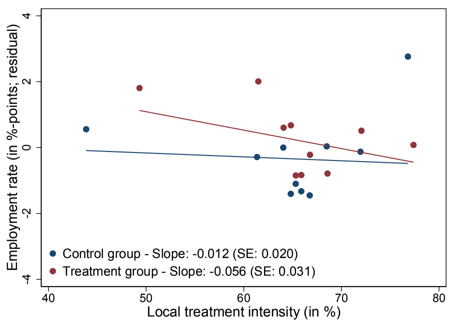


B.3 Total labor earnings within 12m.

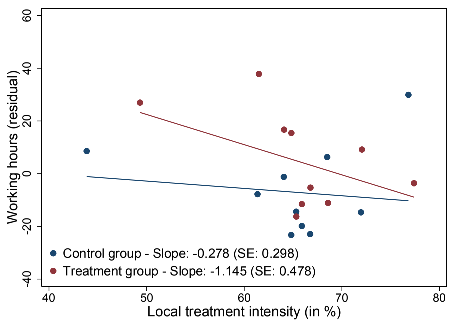


C. Alternative intensity 3 – application portfolio

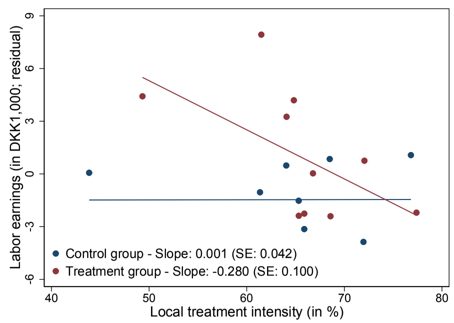
C.1 Avg. employment rate within 12m.



C.2 Total working hours within 12m.



C.3 Total labor earnings within 12m.



Note: The figure depicts a binned scatter plot (with 10 bins) for the relation between local treatment intensities (i.e. the three alternative intensity measures illustrated in Figure B.1) and individual-level labor market outcomes. The relation is shown separately for non-treated (blue line) and treated (red line) job seekers. In each specification, we account for individual characteristics and market-strata fixed effects. Standard errors for the estimates coefficients are clustered at the municipality level (98 clusters).

Table B.1: Balancing test: alternative treatment intensity measures

Dependent variable	Local treatment intensity (0–100)		
	Alternative 1	Alternative 2	Alternative 3
	(1)	(2)	(3)
Age (ref. 18 - 25 years)			
26 - 35 years	0.41	0.33	0.15
	(0.47)	(0.40)	(0.21)
36 - 45 years	0.07	0.06	-0.10
	(0.53)	(0.44)	(0.17)
46 - 55 years	0.19	0.18	-0.01
	(0.61)	(0.50)	(0.21)
56 - 65 years	0.39	0.28	-0.02
	(0.66)	(0.54)	(0.21)
Married	-0.02	0.09	0.17
	(0.23)	(0.18)	(0.12)
Male	0.03	0.00	-0.03
	(0.16)	(0.14)	(0.15)
Any children	0.13	0.01	-0.06
	(0.26)	(0.21)	(0.12)
Danish	-1.76	-1.45	-1.10
	(1.63)	(1.35)	(1.05)
Level of education (ref. no secondary or missing)			
Lower secondary	0.97	0.63	0.06
	(0.86)	(0.71)	(0.23)
Upper secondary	0.90	0.54	0.02
	(0.65)	(0.54)	(0.25)
BA or equivalent	0.62	0.42	0.15
	(0.50)	(0.42)	(0.20)
MA or equivalent	0.50	0.49	0.18
	(0.61)	(0.51)	(0.28)
Elapsed unemployment duration (ref. less than one month)			
1 - 3 months	0.14	0.07	0.13
	(0.19)	(0.15)	(0.11)
4 - 6 months	-0.06	-0.15	-0.18
	(0.20)	(0.16)	(0.13)
7 - 12 months	-0.26	-0.26	-0.21
	(0.38)	(0.32)	(0.18)
13 - 24 months	-0.39	-0.36	-0.26*
	(0.38)	(0.32)	(0.15)
more than 24 months	-0.24	-0.30	-0.38
	(0.58)	(0.48)	(0.37)
Labor earnings in previous year (in DKK 1,000)	0.13	0.16	0.10
	(0.18)	(0.14)	(0.12)
Working hours in previous year (in 1,000)	-0.41	-0.47	-0.28
	(0.43)	(0.35)	(0.29)
Previous occupation (ref. none)			
Managerial position	0.26	0.32	0.09
	(0.59)	(0.47)	(0.21)
Professional position	0.86	0.75	0.39*
	(0.60)	(0.50)	(0.21)
Technicians and associated position	0.83	0.79	0.41
	(0.68)	(0.56)	(0.29)
Clerical support worker	0.71	0.75	0.45
	(0.68)	(0.57)	(0.30)
Service sales worker	0.40	0.37	0.02
	(0.33)	(0.26)	(0.13)
Agricultural worker	1.22	0.98	0.96*
	(0.94)	(0.77)	(0.56)
Craft worker	0.03	-0.09	-0.08
	(0.29)	(0.24)	(0.17)
Plant machine operator	1.21	0.80	0.44
	(0.78)	(0.63)	(0.33)
Elementary occupation	0.59*	0.44	0.19
	(0.34)	(0.28)	(0.14)
Labor market tightness	0.23	-0.03	0.19
	(0.26)	(0.33)	(0.25)
No. of observations	92,098	92,098	90,210
Mean value outcome	64.44	64.44	65.17
P-value joint significance	0.860	0.681	0.345

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 B.2: Differential treatment spillovers

Dependent variable	Avg. monthly emp. rate in %-points	Total working hours	Total labor earnings in DKK
	12m. (1)	12m. (2)	12m. (3)
ADVICE (δ)	1.01** (0.42)	20.95*** (6.88)	4,362*** (1,440)
$\times$ high intensity of occ. recommendations (γ_R)	-1.12** (0.45)	-19.11* (9.43)	-3,867* (2,115)
$\times$ high intensity of vacancy information (γ_V)	0.01 (0.59)	-2.64 (10.17)	203 (2,233)
P-value ($\gamma_R = \gamma_V$)	0.217	0.353	0.305
High intensity of occ. recommendations (α_R)	0.34 (0.41)	3.68 (7.62)	1,525 (1,664)
High intensity of vacancy information (α_V)	-0.047 (0.44)	-0.79 (7.95)	-2,288* (1,334)
P-value ($\alpha_R = \alpha_V$)	0.581	0.741	0.170
No. of observations	90,210	90,210	90,210
Mean value dep. variable	46.74	783.6	143,996
Control variables			
Individual characteristics	Yes	Yes	Yes
Market-strata fixed effects	Yes	Yes	Yes

Note: The table reports results from interacted regressions of treatment indicators and indicators for different levels of local treatment intensities, as specified in Equation (B.2). Separate intensity measures for occupational recommendations and vacancy information are constructed using registered job applications from individuals in the experiment during the two years preceding the intervention. For each market segment (zip code area $\times$ 3-digit-occupation), we compute the share of job seekers who (1) received occupational recommendations (recommendation or combined treatments) or (2) received vacancy information (vacancy or combined treatments). We then construct, for each individual, a weighted average of these segment-level intensities based on their application portfolio (see Appendix B.4). Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/*** indicates statistical significance at the 10%/5%/1%-level.