

The Direct and Indirect Effects of Online Job Search Advice*

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

September 16, 2026

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, Occupational Recommendations, Field Experiment, Spillover Effects, Treatment Externalities, Public Policy

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

*This study was conducted as a part of the research initiative ‘Behavioral Economics and Labor Market Performance’. Financial support by the Danish Ministry of Employment is gratefully acknowledged. We are grateful to Simon Lamech and the team of the Danish Agency for Labor Market and Recruitment for their invaluable support in implementing our study. We thank the editor, Katrine Løken, three anonymous reviewers, and Michèle Belot, Bruno Crépon, Philipp Kircher, Thomas Le Barbanchon, Paul Muller, Roland Rathelot, and Arne Uhlenborff for helpful comments and suggestions. We also thank participants at numerous conferences and seminars for valuable feedback. The experimental design and main research questions were pre-registered at the AEA RCT Registry (AEARCTR-0004014, Altmann *et al.*, 2019).

[†]University of Würzburg, University of Copenhagen and IZA; steffen.altmann@uni-wuerzburg.de

[‡]Danish Agency for Labor Market and Recruitment (STAR); AMG@star.dk

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

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

1 Introduction

Information frictions are a pervasive feature of the job search process. Workers 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, e.g., 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 their core occupations—that is, the occupations listed 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

¹Our 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 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, pooling the three treatment arms. We compare treated and untreated job seekers across regions with different treatment intensities. Advice significantly improves labor market outcomes when the share of treated individuals is moderate: in medium-intensity regions (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 relative to the control group. Over 12 months, positive effects remain for cumulative working hours and earnings, while employment effects are no longer statistically significant. At the same time, we document substantial treatment spillovers among treated job seekers. In high-intensity regions (where 90% of job seekers receive advice), treated individuals have 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 markets (e.g., accounting for inter-municipal commuting flows) and are large enough to fully offset the positive direct effects of advice at high treatment intensity.

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).

Registered job applications show that the positive effects in medium-intensity regions are accompanied by a shift in search toward occupations with better job opportunities and lower competition. As more job seekers receive advice, however, these effects on occupational competition reverse, creating congestion in the newly targeted occupations.

Spillover effects on job seekers in the control group are small and statistically insignificant on average, but vary systematically across occupations and regions. Consistent with the reallocation of search effort across occupations, high treatment intensity tends to generate positive spillovers for untreated job seekers whose core occupations experience reduced competition from treated job seekers, but negative spillovers for those whose core occupations become more crowded. A similar pattern emerges across regions: spillovers at high treatment intensity tend to be positive in regions where initial tightness is distributed relatively unevenly across occupations, but negative where it is distributed relatively evenly. These patterns suggest that spillovers arise because treated job seekers change which occupations they target, thereby altering the competitive pressure faced by untreated job seekers.

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.

The central contribution of our paper is to demonstrate that the effectiveness of online job search advice depends on the scale at which it is implemented. Using randomized variation in treatment intensity across local labor markets, we show that advice increases employment and earnings when provided to a limited share of job seekers, but that these gains disappear as a larger share of job seekers receives advice. Detailed application data and the heterogeneous pattern of spillovers indicate that this attenuation operates through the reallocation of search across occupations: when similar advice is provided to many job seekers, the resulting shifts in search alter occupation-specific competition and generate congestion. The same mechanism produces heterogeneous spillovers on untreated job seekers, benefiting those whose core occupations face less competition and harming those whose occupations become more crowded.

Existing studies on online job search advice provide promising evidence that advice can improve labor market outcomes. Occupational referrals broaden search and increase job interviews (Belot *et al.*, 2019), while also improving employment among the long-term unemployed (Belot *et al.*, 2026) and job seekers in structurally weak labor markets (Belot *et al.*, 2025). Studies of recommender systems directing job seekers toward specific job ads or firms find modest increases in employment and transitions into short-term contracts, respectively (Le Barbanchon *et al.*, 2023; Behaghel *et al.*, 2024).² Most of this literature estimates the effects of advice at a fixed level of treatment coverage. Le Barbanchon *et al.* (2023) and Behaghel *et al.* (2024) examine congestion around recommended vacancies or firms, finding limited evidence of congestion. By randomly

²Ben Dhia *et al.* (2026), by contrast, find no employment effects from encouraging job seekers to use a privately operated job search assistance website.

varying treatment coverage across markets between medium and high levels, our design directly identifies whether the employment and earnings effects of advice change as coverage rises. We find that they do. The positive effects observed at moderate treatment intensity are fully offset at high intensity.

Beyond the literature on online advice, our study relates to broader work on job search assistance, counseling, and information provision (e.g., Behaghel *et al.* 2014, Bennismarker *et al.* 2013, Schiprowski 2020, Altmann *et al.* 2018, 2022; for overviews, see also Card *et al.* 2010, 2017, Le Barbanchon *et al.* 2024). A distinctive feature of our study is that we combine randomized variation in advice and treatment coverage with detailed records of job applications and labor market outcomes, allowing us to trace how advice reallocates search across occupations and relate these shifts to subsequent employment and earnings. A methodologically related study is Kuhn and Shen (2023), who use linked job-ad, application, and callback data to examine the effects of removing explicit gender requests from job postings on application behavior and employer callbacks.

Our findings also contribute to the literature on spillovers and equilibrium effects of policy interventions across different policy domains. Within labor economics, some studies of traditional job search and placement assistance programs document displacement effects, whereby gains for treated job seekers may come partly at the expense of untreated workers competing for the same jobs (Crépon *et al.*, 2013; Gautier *et al.*, 2018; Cheung *et al.*, 2025).³ Our findings provide evidence of a distinct spillover margin: advice redirects search across occupations and redistributes competitive pressure across them. This reallocation can generate both losses and gains for untreated job seekers, depending on how competition in their core occupations changes (see also Kircher, 2022). Research in other policy domains similarly shows that treatment externalities and equilibrium responses can alter the overall effects of interventions, for instance in the context of health programs (Miguel and Kremer, 2004) or cash transfers (Angelucci and De Giorgi, 2009; Egger *et al.*, 2022). Our findings thus reinforce the general lesson that treatment effects estimated under partial implementation need not extrapolate to large-scale roll-out (Muralidharan and Niehaus, 2017; Al-Ubaydli *et al.*, 2017, 2019).

³Related work studies equilibrium effects of a broader range of labor market policies (Albrecht *et al.*, 2009; Lalive *et al.*, 2015; Lise *et al.*, 2004; Muralidharan *et al.*, 2023).

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.*, 2026), Sweden (Le Barbanchon *et al.*, 2023), and France (Behaghel *et al.*, 2024), 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 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

⁴Independent 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.

⁵We use register data covering all unemployment-to-job transitions in Denmark from 2013 to 2016 and augment these data with information on current vacancies and educational overlap across occupations. This ensures that recommendations exclude occupations without available vacancies or those requiring education beyond the job seeker's qualifications. To assess whether transition patterns from 2013–2016 remain informative for the 2019 experiment, we examine their stability over time. Year-to-year correlations in occupational transition rankings exceed 0.85 over the 2013–2019 period, as do correlations in local vacancy counts at the occupation-by-municipality level.

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 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
Any advice	(1) Control group	Generic: search profile (C)	Generic: video (D)
	(2) Recommendation treatment	Recommendation card (A)	Generic: video (D)
	(3) Vacancy treatment	Vacancy card (B)	Generic: video (D)
	(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				No. of individuals
		Control group	Recom. treatment	Vacancy treatment	Combined treatment	
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 characteristics

All individuals who were registered as unemployed and received UI benefits on March 15, 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 combine the experimental data (STAR, 2020a) with individual-level information from several additional data sources. First, we exploit comprehensive register data administered by Statistics Denmark on socio-demographic characteristics and individuals' labor market outcomes (DST, 2023). 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 (STAR, 2020b) and from the vacancy database on the job search platform administered by the public employment service (STAR, 2020d). 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, called *joblog* (STAR, 2020c). 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'

⁶Notably, 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.

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 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 our results, we outline the potential direct and indirect effects of advice within an occupational search framework (see also Belot *et al.*, 2019; Kircher, 2022). We first examine how occupational recommendations and vacancy information affect search behavior and employment, and how combining them may amplify or offset their separate effects. We then discuss how job seekers' responses to advice can generate spillovers for others.

Model setup: We consider an economy with a population N of unemployed job seekers of types $i \in \{1, \dots, I\}$, who allocate search effort across occupations $k \in \{1, \dots, K\}$. Let $s_{ik} \geq 0$ denote the effort a type- i job seeker devotes to occupation k . Job seekers differ in how well their skills match each occupation, captured by the skill alignment $\phi_{ik} \in [0, 1]$.

The number of matches in occupation k follows the matching function $m(u_k, v_k)$, which is increasing and concave in posted vacancies v_k and in aggregate search effort $u_k = \sum_i^N s_{ik}$ (see, e.g., Pissarides, 2000; Michaillat, 2012; Crépon *et al.*, 2013). Labor

⁷Fluchtmann *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.

market conditions in occupation k are summarized by tightness $\theta_k = v_k/u_k$. The rate at which a type- i job seeker who exerts effort s_{ik} receives an offer in occupation k is then

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

with $q(\theta_k)$ increasing and concave. Search is costly, with the cost function $\gamma(s_{ik}, s_{i-k})$ being convex in effort and exhibiting cross-occupation crowding, such that greater effort in one occupation raises the marginal cost of effort in others ($\partial^2\gamma/\partial s_{ik}\partial s_{i-k} > 0$). The value of employment, $V_{ik}(\phi_{ik}, \theta_k)$, increases in skill alignment ϕ_{ik} and in tightness θ_k —the latter because workers facing less competition can bargain for better job characteristics, such as higher wages or more stable employment. Unemployment yields instantaneous utility b .

Optimal search strategy: Job seekers maximize the present value of income over an infinite horizon with discount rate ρ . Letting U_i denote the value of unemployment for a type- i worker,

$$\rho U_i = \max_{s_{i1}, \dots, s_{iK}} \left[b + \sum_k \{ \lambda_{ik}(\phi_{ik}, s_{ik}, \theta_k) \max \{ V_{ik}(\phi_{ik}, \theta_k) - U_i, 0 \} - \gamma(s_{ik}, s_{i-k}) \} \right]. \quad (2)$$

The flow value of unemployment combines utility b , the expected gain from an offer in each occupation—received at rate λ_{ik} and worth $\max\{V_{ik} - U_i, 0\}$ —and search costs $\gamma(\cdot)$. The optimal effort vector $s_i^* = (s_{i1}^*, \dots, s_{iK}^*)$ balances the return to search against its cost in each occupation, as characterized by the first-order condition for effort in occupation k :

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

The left-hand side is the marginal benefit of search in occupation k , rising with skill alignment, tightness, and the surplus $V_{ik} - U_i$; the right-hand side is the marginal cost, which depends on effort in all other occupations, s_{i-k} . For any occupation k where effort is positive, the two are equal; in occupations where the marginal return at zero effort falls short of the marginal cost, the job seeker exerts no effort (a corner solution). A higher θ_k or ϕ_{ik} raises the marginal return in occupation k and hence optimal effort s_{ik} . Through cross-occupation crowding, the resulting increase in s_{ik} raises the marginal cost of search in other occupations and thereby reduces s_{i-k} .

3.1 Redirecting job search across occupations

The aim of the advice is to help job seekers allocate search effort across occupations more effectively. We assume job seekers hold subjective beliefs about their skill alignment, $\hat{\phi}_{ik}$, and about occupation-specific tightness, $\hat{\theta}_k$, and choose effort to maximize (2) given these beliefs. The two forms of advice operate through these beliefs: occupational recommendations update $\hat{\phi}_{ik}$, and vacancy information updates $\hat{\theta}_k$ (see Section 2.1). By the first-order condition (3), any update that raises the perceived marginal return to search in an occupation raises effort there and, through cross-occupation crowding, lowers it elsewhere. The resulting reallocation can improve both job finding (through λ) and match quality (through V). Section 3.2 then discusses the externalities this reallocation generates for other job seekers.

Following Kircher (2022), we illustrate the two channels with two occupations $k \in \{1, 2\}$ and two worker types $i \in \{1, 2\}$, where a worker's type denotes the core occupation listed in their search profile at baseline. Absent advice, each type searches most intensively in their core occupation ($s_{11} \geq s_{12}$ and $s_{22} \geq s_{21}$).⁸

Recommendations update skill alignment (ϕ): Suppose tightness is equal across occupations ($\theta_2 = \theta_1$) and type-1 workers search mostly in occupation 1 because they believe that their skills are better aligned there ($\hat{\phi}_{11} > \hat{\phi}_{12}$), while underestimating their fit for occupation 2 ($\hat{\phi}_{12} \leq \phi_{12}$). This belief may, for instance, reflect their previous employment in occupation 1. A recommendation for occupation 2 signals that their skills are better aligned with that occupation than they initially believed, thereby redirecting effort toward occupation 2. If job seekers follow the recommendation, the resulting employment gains arise mainly in recommended occupations.

Vacancy information updates tightness (θ): Now suppose workers' skills are equally well aligned with both occupations ($\phi_{i1} = \phi_{i2}$ for $i \in \{1, 2\}$), but each type searches mostly in its core occupation because they perceive that occupation to be tighter ($\hat{\theta}_1 > \hat{\theta}_2$ for type 1, and the reverse for type 2). Suppose further that both types misperceive the true tightness of their core occupation: type-1 workers overestimate it ($\hat{\theta}_1 > \theta_1$), whereas type-2 workers underestimate it ($\hat{\theta}_2 < \theta_2$). Vacancy information updates these

⁸Consistent 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.

biased beliefs about occupation-specific tightness. Type-1 workers shift effort *away* from their core occupation, so additional employment arises outside it. Type-2 workers shift effort *toward* their core occupation, so additional employment arises within it.

The two channels can reinforce or offset: Vacancy information and occupational recommendations can have complementary effects when both signals point in the same direction, thereby amplifying the response. Workers reallocate search more strongly when they learn both that their core occupation has fewer openings than expected *and* that their skills are better aligned with the alternative than previously thought.⁹ When the signals point in different directions—for example, when the core occupation has more vacancies than expected, while the recommendation indicates better-than-expected skill alignment with an alternative—the effects partly offset each other. If the marginal cost of reallocating effort is high, the worker may not adjust search at all.¹⁰

3.2 Externalities on other job seekers

The previous section illustrated how advice can lead job seekers to reallocate search effort across occupations, with treated job seekers shifting effort from occupation 1 to occupation 2 in our examples. As more individuals receive advice and adjust their search, however, this reallocation changes labor market tightness and thereby generates externalities for 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 effort accordingly, labor market tightness in the absorbing occupation (occupation 2 in the scenarios above), θ_2 , decreases. This implies that treated type-1 job seekers who shift to occupation 2 experience weaker employment effects as the share of treated individuals rises. Consequently, advice should be less effective in regions with high treatment intensity than in regions with medium intensity.

⁹With more than two occupations, receiving both types of advice may help job seekers update perceived labor demand in their core occupation while steering them toward the alternative occupation with the highest skill alignment.

¹⁰In principle, job seekers could raise overall effort, but this is unlikely when marginal search costs are high; in the extreme, total effort is fixed.

Externalities on non-treated job seekers: For non-treated job seekers, the sign of the spillover depends on how the intervention alters labor market tightness in their core occupations. Non-treated type-2 job seekers, who predominantly search in occupation 2, are made worse off by the increased competition as more treated individuals shift effort into that occupation. Non-treated type-1 job seekers, by contrast, may benefit from higher treatment intensity: as treated workers move toward occupation 2, tightness in their core occupation 1 rises, improving the prospects of those who continue to search there.

Moreover, the externalities experienced by untreated job seekers may also depend on whether tightness is initially equal across occupations. Because the matching function is concave, the number of matches is maximized when 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 occupation 2 improves labor market prospects for those who continue searching 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 share 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:

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

where 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

¹¹Note 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.

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 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.

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), the treatment effects on employment, working hours, and earnings are substantially smaller in high-intensity than in medium-intensity regions. These negative spillover effects among treated job seekers are most pronounced during the first six months, although the γ -coefficients remain consistently negative throughout the observation period. The spillovers are large enough to fully offset the positive effects of advice at high treatment intensities. In high-intensity regions, the estimated differences in employment and earnings between treated and untreated job seekers, $\delta + \gamma$, are slightly negative, although generally not statistically significant (see the tests of $\delta + \gamma = 0$ in Table 3). Overall, these results demonstrate that advice generates negative spillovers among treated job seekers.

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

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)
A. Treatment effects and high-intensity spillovers among treated job seekers						
ADVICE (δ)	0.88** (0.41)	0.45 (0.31)	8.75** (3.35)	11.03* (5.60)	1,858*** (667)	2,626** (1,074)
× high-intensity (γ)	-1.61** (0.62)	-0.79 (0.59)	-12.21** (5.09)	-10.73 (10.68)	-3,384*** (1,058)	-4,203* (2,134)
P -value ($\delta + \gamma = 0$) ^(a)	0.113	0.500	0.364	0.968	0.068	0.397
B. Treatment-intensity regime effects (ref. super-control)						
Medium-intensity (α_M)	-0.60 (1.05)	-0.50 (0.80)	-3.95 (8.06)	-9.03 (11.71)	31 (1,414)	365 (2,058)
High-intensity (α_H)	0.94 (1.02)	0.58 (0.89)	4.40 (7.98)	2.63 (14.16)	2,055 (1,368)	3,188 (2,244)
P -value ($\alpha_M = \alpha_H = 0$) ^(b)	0.322	0.403	0.619	0.615	0.279	0.359
Observations	92,098	92,098	92,098	92,098	92,098	92,098
Mean value super-control	41.67	47.00	338.2	787.5	62,116	145,013

Note: The table examines the effects of job search advice on labor market outcomes, pooling the three treatment arms, and how these effects vary with local treatment intensity. It reports results from interacted regressions of a pooled treatment indicator and local treatment-intensity regimes, as described by Equation (4), estimated for the full experimental population. All specifications include individual controls and market-strata fixed effects. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/** indicate statistical significance at the 10%/5%/1%-level.

^(a)The p -values test the statistical significance of the sum of the treatment coefficient and its interaction with the high-intensity regime indicator. This sum corresponds to the difference between treated and control job seekers within high-intensity regions.

^(b)The p -values test the null hypothesis that the coefficients on the medium- and high-intensity regime indicators are jointly equal to zero. This test captures whether control-group outcomes differ systematically across treatment-intensity regimes relative to the super-control group.

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 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

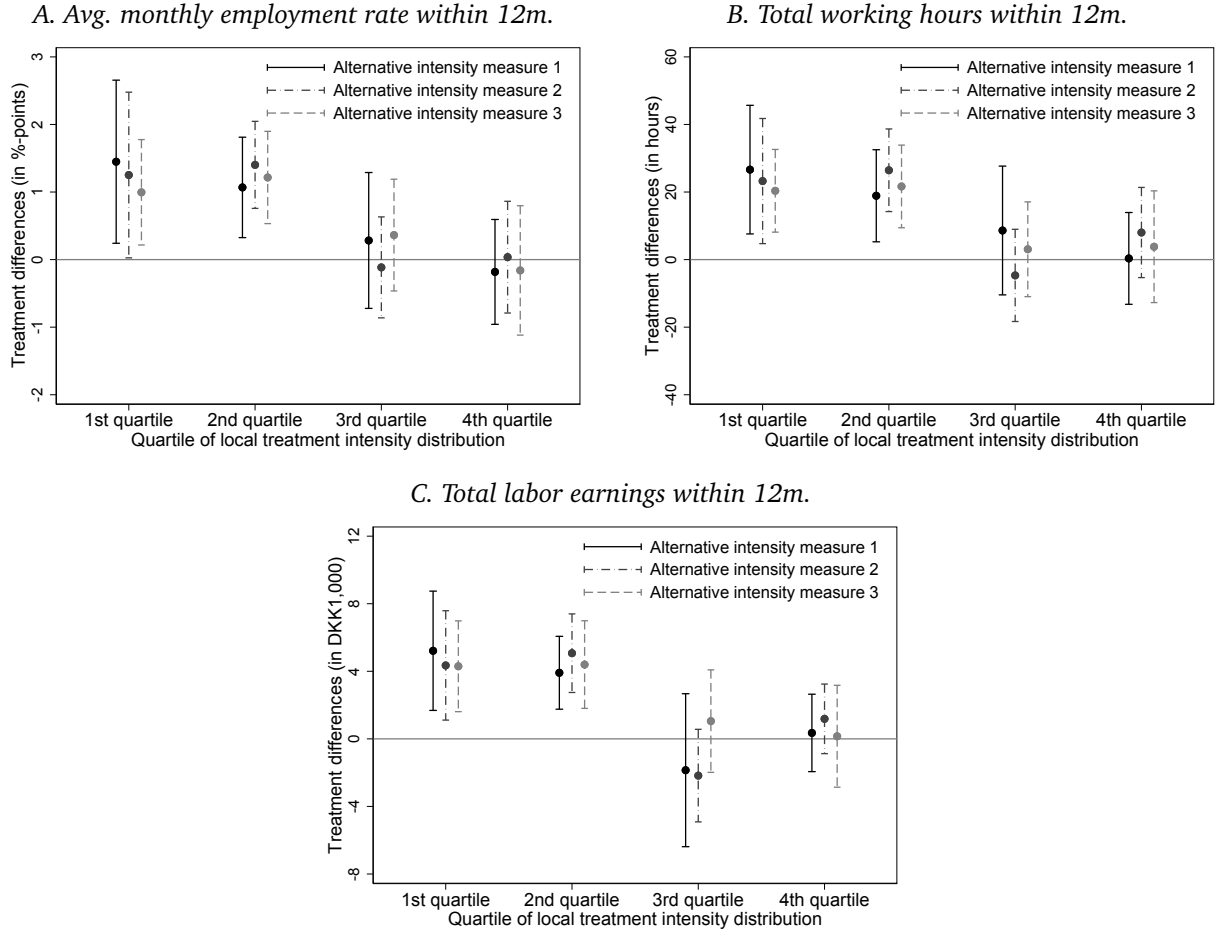
For each of the three alternative measures of treatment intensity, Figure 1 displays treatment effects on our three main outcomes—measured over a 12-month time horizon—across quartiles of the respective treatment-intensity distributions. The results closely mirror our main findings from Table 3. We consistently 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

Next, 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

¹²As 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.

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.

Table 4: Shifts in occupational competition

Dependent variable	Log average no. of applications per vacancy in occupations applied to ^(a)		
	1m. (1)	6m. (2)	12m. (3)
A. Treatment effects and high-intensity spillovers among treated job seekers			
ADVICE (δ)	-0.048** (0.021)	-0.059** (0.028)	-0.033 (0.026)
× high intensity (γ)	0.114** (0.051)	0.067 (0.048)	0.025 (0.049)
P -value ($\delta + \gamma = 0$) ^(b)	0.162	0.833	0.848
B. Treatment-intensity regime effects (ref. super-control)			
Medium intensity (α_M)	0.031 (0.084)	-0.056 (0.080)	-0.076 (0.080)
High intensity (α_H)	-0.068 (0.092)	-0.050 (0.079)	-0.049 (0.078)
P -value ($\alpha_M = \alpha_H = 0$) ^(c)	0.449	0.758	0.640
Observations	82,957	85,994	87,606

Note: The table examines the effects of job search advice on occupational competition, pooling the three treatment arms, and how these effects vary with local treatment intensity. It reports results from interacted regressions of a pooled treatment indicator and local treatment-intensity regimes, as described by Equation (4), estimated for the full experimental population. All specifications include individual controls and market-strata fixed effects. Standard errors in parenthesis are clustered at the municipality level (98 clusters). */**/** indicate 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.

^(b)The p -values test the statistical significance of the sum of the treatment coefficient and its interaction with the high-intensity regime indicator. This sum corresponds to the difference between treated and control job seekers within high-intensity regions.

^(c)The p -values test the null hypothesis that the coefficients on the medium- and high-intensity regime indicators are jointly equal to zero. This test captures whether control-group outcomes differ systematically across treatment-intensity regimes relative to the super-control group.

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 treatment effect on occupational competition reverses as the treatment intensity increases. The positive γ -coefficient indicates that the lower competition faced by treated relative to untreated job seekers in medium-intensity regions is significantly eroded—and numerically reversed—in high-intensity regions. This pattern supports the interpretation 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

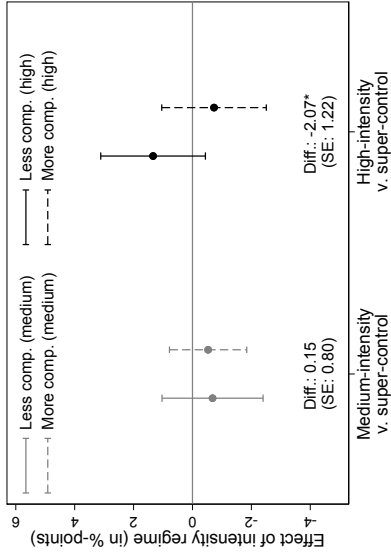
While our results so far indicate that, on average, the labor market outcomes of untreated job seekers are not affected by the intervention, the framework discussed in Section 3 suggests that treatment spillovers on untreated job seekers may vary systematically across subgroups of control job seekers. We examine two dimensions of heterogeneity. The first is occupation-specific: spillovers may depend on how the intervention changes competition in the occupations that control-group job seekers target. The second is region-specific: spillovers may depend on whether initial tightness is evenly or unevenly distributed across occupations within a region. In this subsection, we empirically test these two hypotheses.

Occupation-specific heterogeneity: changes in competition in core occupations We begin with the occupation-specific dimension of heterogeneity. Specifically, we examine how changes in competition in the core occupations of control-group job seekers shape

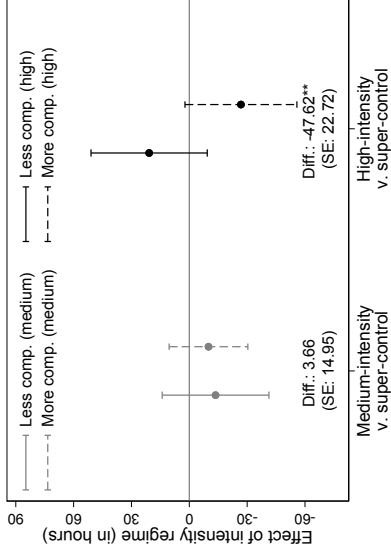
Figure 2: Heterogeneous spillover effects on the control group

A. Heterogeneity by change of competition in core occupations

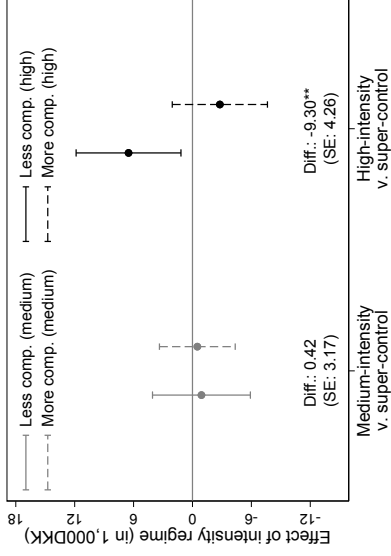
A.1 Avg. monthly employment rate within 12m.



A.2 Total working hours within 12m.

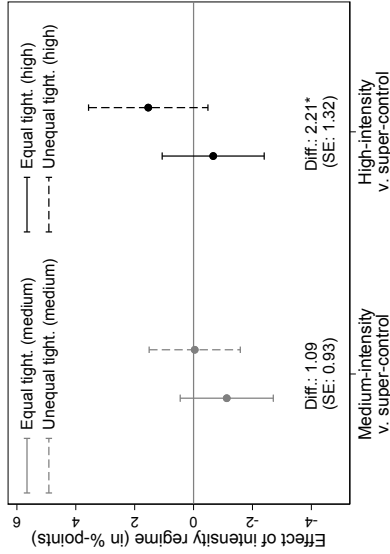


A.3 Total labor earnings within 12m.

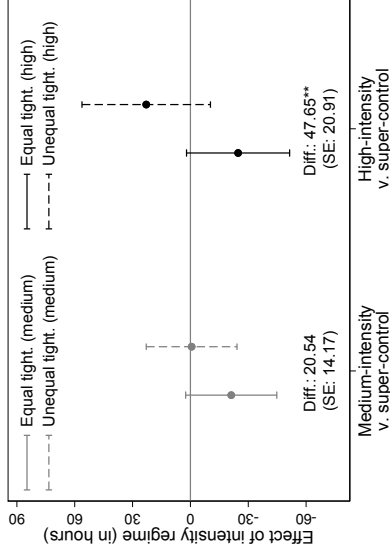


B. Heterogeneity by variance of labor market tightness

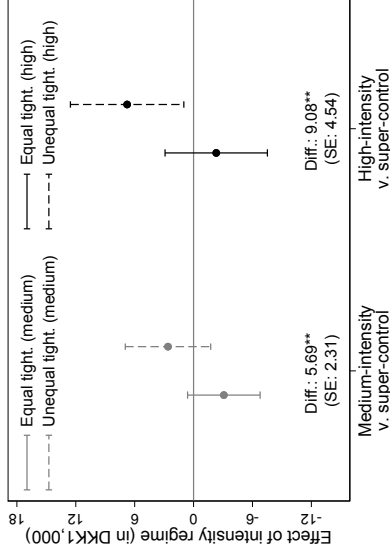
B.1 Avg. monthly employment rate within 12m.



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.

treatment spillovers. We measure changes in occupational competition by comparing the number of applications submitted by treated job seekers to a given occupation in the post-intervention period with the corresponding number in the pre-intervention period. This measure is constructed at the national level and uses applications from individuals in the treatment groups within three-month windows before and after the start of the experiment. Based on this measure, the distribution of which is shown in Appendix Figure A.4, we distinguish between *control-group* job seekers whose core occupations experience decreasing competition from treated job seekers and those whose core occupations experience increasing competition. We then examine heterogeneous spillover effects by estimating separate regressions for the two groups:

$$Y_{ij} = \gamma_M TI_j^{\text{Med}} + \gamma_H TI_j^{\text{High}} + X_i \Pi + \varepsilon_{ij}. \quad (5)$$

Panel A of Figure 2 depicts the resulting coefficients γ_M and γ_H , which capture the effects of assignment to the medium- and high-intensity regimes, respectively. Solid lines refer to control-group job seekers whose core occupations experience declining competition, while dashed lines refer to those whose core occupations experience increasing competition.

We find that spillovers on untreated job seekers depend systematically on how the intervention changes 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 (see the red solid and dashed lines in Panel A of Figure 2). The differences in spillover effects across occupations with decreasing versus increasing competition 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 become more crowded exhibit a mild decline in earnings (Panel A.3). Qualitatively similar patterns emerge for employment rates and working hours. The main patterns also persist when using an alternative measure of changes in occupational competition (Appendix Figure A.5). 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, regardless 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. One interpretation is that the induced shifts in search behavior are not large enough at intermediate treatment intensities to generate systematic changes in competitive pressure for untreated job seekers. 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.

Region-specific heterogeneity: the distribution of tightness across occupations We next turn to the region-specific dimension of heterogeneity. Specifically, 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 unevenly distributed across occupations, as implied by 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. We then estimate Equation (5) separately for the two resulting groups. Panel B of Figure 2 shows the results. Solid lines refer to control-group job seekers located in regions with a relatively equal tightness distribution across occupations, while dashed lines refer to those located in regions with a relatively unequal distribution. Appendix Figure A.5 presents a corresponding robustness check based on an alternative measure of labor-market tightness.

We find that treatment spillovers on untreated job seekers vary systematically with the distribution of initial labor-market tightness 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. These patterns 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, our results 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

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)
A. Treatment effects and high-intensity spillovers among treated job seekers						
Recommendation treatment (δ_{Rec})	1.10*** (0.39)	0.32 (0.37)	10.05*** (3.33)	7.32 (7.28)	2,356*** (679)	2,560* (1,538)
× high intensity (γ_{Rec})	-1.99*** (0.61)	-0.98 (0.68)	-14.05*** (5.26)	-12.63 (12.37)	-3,633*** (1,159)	-4,849* (2,520)
P -value ($\delta_{\text{Rec}} + \gamma_{\text{Rec}} = 0$) ^(a)	0.063	0.244	0.328	0.595	0.179	0.257
Vacancy treatment (δ_{Vac})	1.05* (0.57)	1.01** (0.43)	11.05** (4.40)	21.17*** (6.92)	2,048** (942)	4,061*** (1,499)
× high intensity (γ_{Vac}) ^(a)	-1.62** (0.80)	-0.98 (0.68)	-13.40** (6.39)	-13.56 (12.12)	-3,565*** (1,356)	-4,739* (2,554)
P -value ($\delta_{\text{Vac}} + \gamma_{\text{Vac}} = 0$)	0.319	0.956	0.614	0.446	0.126	0.744
Combined treatment (δ_{Com}) ^(a)	0.48 (0.60)	0.02 (0.47)	5.06 (5.29)	2.82 (9.16)	1,162 (1,140)	837 (1,759)
× high intensity (γ_{Com})	-1.23 (0.82)	-0.42 (0.77)	-9.28 (6.90)	-4.02 (13.75)	-2,963** (1,457)	-2,586 (2,704)
P -value ($\delta_{\text{Com}} + \gamma_{\text{Com}} = 0$) ^(a)	0.200	0.524	0.358	0.908	0.057	0.403
B. Treatment-intensity regime effects (ref. super-control)						
Medium intensity (α_M)	-0.60 (1.05)	-0.50 (0.80)	-3.96 (8.06)	-8.88 (11.72)	30 (1,414)	377 (2,048)
High intensity (α_H)	0.93 (1.02)	0.58 (0.89)	4.44 (7.98)	2.76 (14.15)	2,061 (1,369)	3,182 (2,235)
P -value ($\alpha_M = \alpha_H = 0$) ^(a)	0.322	0.403	0.616	0.619	0.277	0.357
C. Equality tests: differential treatment effects (p-values)^(c)						
$\delta_{\text{Rec}} = \delta_{\text{Vac}}$	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
D. Equality tests: differential high-intensity spillovers (p-values)^(d)						
$\gamma_{\text{Rec}} = \gamma_{\text{Vac}}$	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
Observations	92,098	92,098	92,098	92,098	92,098	92,098
Mean value super-control group	41.67	47.00	338.2	787.5	62,116	145,013

Note: The table examines the effects of different types of job search advice on labor market outcomes and how these effects vary with local treatment intensity. It reports results from interacted regressions of indicators for the three treatment arms and local treatment-intensity regimes, as described by Equation (4), estimated for the full experimental population. All specifications include individual controls and market-strata fixed effects. Standard errors in parentheses are clustered at the municipality level (98 clusters). */**/** indicate statistical significance at the 10%/5%/1% level.

^(a)The p -values test the statistical significance of the sum of the treatment coefficient and its interaction with the high-intensity regime indicator. This sum corresponds to the difference between treated and control job seekers within high-intensity regions.

^(b)The p -values test the null hypothesis that the coefficients on the medium- and high-intensity regime indicators are jointly equal to zero. This test captures whether control-group outcomes differ systematically across treatment-intensity regimes relative to the super-control group.

^(c)The p -values test the null hypothesis of equal treatment effects across treatment arms within medium-intensity regions, measured relative to the control group.

^(d)The p -values test the null hypothesis that the high-intensity interaction effects are equal across treatment arms. These interaction effects measure spillovers relative to the medium-intensity regime.

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 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 the effects of occupational recommendations and vacancy information on employment rates, working hours, and labor earnings are significantly smaller at higher treatment intensities. This finding reinforces our earlier evidence that negative 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.

¹³In 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.

¹⁴This 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.

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 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** (0.32)	-0.55** (0.27)	0.60** (0.29)	0.29 (0.25)	0.77** (0.37)	0.44 (0.35)
Vacancy treatment (δ_{Vac})	0.91*** (0.32)	0.46* (0.27)	-0.13 (0.29)	-0.29 (0.25)	0.68* (0.37)	0.40 (0.35)
Combined treatment (δ_{Com})	0.60* (0.32)	0.35 (0.27)	0.42 (0.29)	0.19 (0.25)	0.68* (0.37)	0.48 (0.35)
<i>P</i> -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.

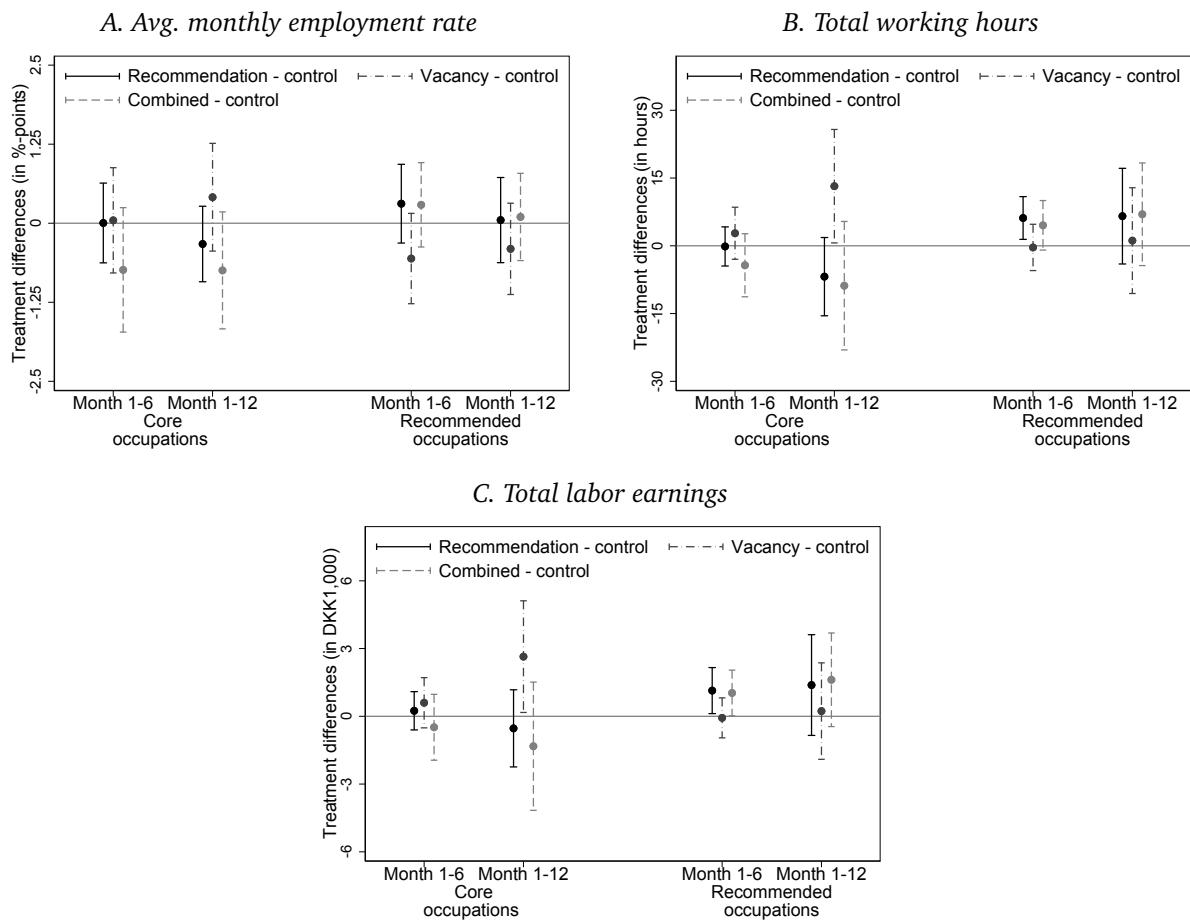
These effects are consistent with the idea that occupational recommendations convey information about skill alignment, thereby increasing job seekers' perceived returns to searching in the recommended occupations and encouraging them to redirect search effort accordingly. In line with this interpretation, 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

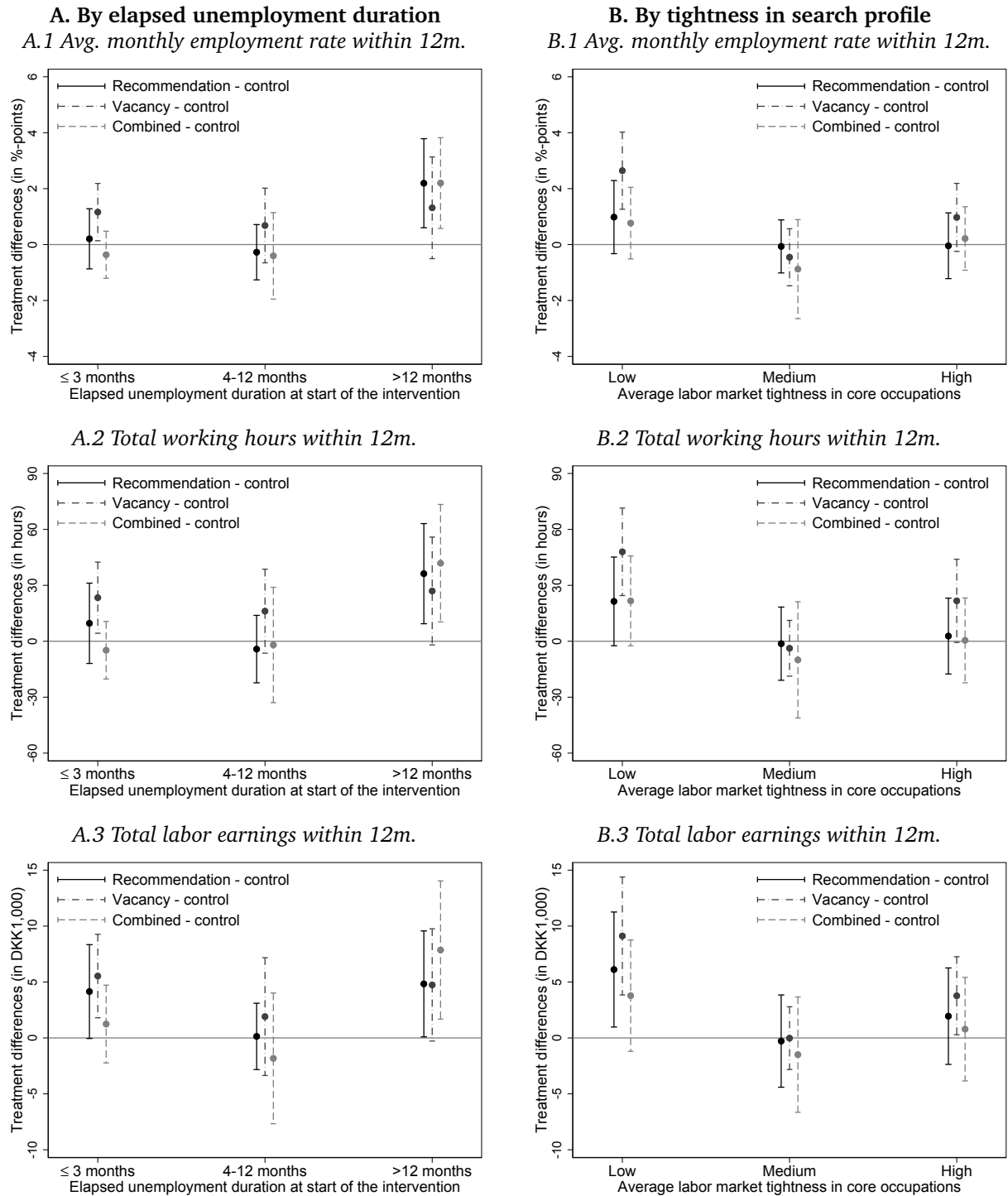
Heterogeneity by labor market tightness: Panel B of Figure 4 illustrates that occupational recommendations and vacancy information tend to be particularly effective for job seekers facing unfavorable labor market conditions. Among individuals in the lowest tercile of the occupational tightness distribution, 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

¹⁵The 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 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.

¹⁶When 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.

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.

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 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.* (2025) and Belot *et al.* (2026), 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.

Data Availability

The individual-level data underlying the results in this article are confidential and cannot be publicly shared. Details on data access and replication materials are provided in the documentation on Zenodo: <https://doi.org/10.5281/zenodo.22044170>

References

- AL-UBAYDLI, O., J. A. LIST, D. LORE, AND D. SUSKIND (2017): “Scaling for economists: Lessons from the non-adherence problem in the medical literature,” *Journal of Economic Perspectives*, 31, 125–44.
- AL-UBAYDLI, O., J. A. LIST, AND D. SUSKIND (2019): “The science of using science: Towards an understanding of the threats to scaling experiments,” NBER Working Paper No. w25848.
- ALBRECHT, J., G. J. VAN DEN BERG, AND S. VROMAN (2009): “The aggregate labor market effects of the Swedish knowledge lift program,” *Review of Economic Dynamics*, 12, 129–146.
- ALTMANN, S., S. CAIRO, R. MAHLSTEDT, AND A. SEBALD (2022): “Do Job Seekers Understand the UI Benefit System (and Does It Matter)?” *IZA Discussion Paper No. 15747*.
- ALTMANN, S., A. FALK, S. JAEGER, AND F. ZIMMERMANN (2018): “Learning about Job Search: A Field Experiment with Job Seekers in Germany,” *Journal of Public Economics*, 164, 33–49.
- ALTMANN, S., A. GLENNY, R. MAHLSTEDT, AND A. SEBALD (2019): “Digital Tools to Facilitate Job Search,” AEA RCT Registry. AEARCTR-0004014, <https://www.socialscisciregistry.org/trials/4014>.
- ANGELUCCI, M. AND G. DE GIORGI (2009): “Indirect effects of an aid program: how do cash transfers affect ineligibles’ consumption?” *American Economic Review*, 99, 486–508.
- BAIRD, S., J. A. BOHREN, C. MCINTOSH, AND B. ÖZLER (2018): “Optimal design of experiments in the presence of interference,” *Review of Economics and Statistics*, 100, 844–860.
- BEHAGHEL, L., B. CRÉPON, AND M. GURGAND (2014): “Private and public provision of counseling to job seekers: Evidence from a large controlled experiment,” *American Economic Journal: Applied Economics*, 6, 142–74.
- BEHAGHEL, L., S. DROMUNDO MOKRANI, M. GURGAND, Y. HAZARD, AND T. ZUBER (2024): “The Potential of Recommender Systems for Directing Job Search: A Large-Scale Experiment,” *IZA Discussion Paper No. 16781*.
- BELOT, M., B. DE KONING, D. FOURAGE, P. KIRCHER, P. MULLER, AND S. PHILIPPEN (2025): “Advising Job Seekers in Occupations with Poor Prospects: A Field Experiment,” *IZA Discussion Paper No. 17905*.
- BELOT, M., P. KIRCHER, AND P. MULLER (2019): “Providing advice to jobseekers at low cost: An experimental study on online advice,” *Review of Economic Studies*, 86, 1411–1447.

- (2026): “Do the long-term unemployed benefit from automated occupational advice during online job search?” *The Economic Journal*, 136, 184–206.
- BEN DHIA, A., B. CRÉPON, E. MBIH, L. PAUL-DELVAUX, B. PICARD, AND V. PONS (2026): “Can a Digital Job Search Coach Reduce Unemployment? Experimental Evidence from France,,” *Journal of Labor Economics*, forthcoming.
- BENNMARKER, H., E. GRÖNQVIST, AND B. ÖCKERT (2013): “Effects of contracting out employment services: Evidence from a randomized experiment,” *Journal of Public Economics*, 98, 68–84.
- CARD, D., J. KLUVE, AND A. WEBER (2010): “Active labour market policy evaluations: A meta-analysis,” *The Economic Journal*, 120, F452–F477.
- (2017): “What works? A meta analysis of recent active labor market program evaluations,” *Journal of the European Economic Association*, 16, 894–931.
- CHEUNG, M., J. EGEBAK, A. FORSLUND, L. LAUN, M. RÖDIN, AND J. VIKSTRÖM (2025): “Does job search assistance reduce unemployment? Evidence on displacement effects and mechanisms,” *Journal of Labor Economics*, 43, 47–81.
- CRÉPON, B., E. DUFLO, M. GURGAND, R. RATHELOT, AND P. ZAMORA (2013): “Do labor market policies have displacement effects? Evidence from a clustered randomized experiment,” *The Quarterly Journal of Economics*, 128, 531–580.
- DST (2023): “Employment for Employees Register (BFL) [Beskæftigelse for Lønmodtagere],” Copenhagen: Statistics Denmark, data accessed through Statistics Denmark’s Research Service.
- EGGER, D., J. HAUSHOFER, E. MIGUEL, P. NIEHAUS, AND M. WALKER (2022): “General equilibrium effects of cash transfers: experimental evidence from Kenya,” *Econometrica*, 90, 2603–2643.
- FLUCHTMANN, J., A. M. GLENNY, N. HARMON, AND J. MAIBOM (2024): “Unemployed job search across people and over time: Evidence from applied-for jobs,” *Journal of Labor Economics*, 42, 1175–1217.
- GAUTIER, P., P. MULLER, B. VAN DER KLAUW, M. ROSHOLM, AND M. SVARER (2018): “Estimating equilibrium effects of job search assistance,” *Journal of Labor Economics*, 36, 1073–1125.
- GIBBONS, R., L. F. KATZ, T. LEMIEUX, AND D. PARENT (2005): “Comparative advantage, learning, and sectoral wage determination,” *Journal of Labor Economics*, 23, 681–724.
- GIBBONS, R. AND M. WALDMAN (1999): “A theory of wage and promotion dynamics inside firms,” *The Quarterly Journal of Economics*, 114, 1321–1358.
- GOLDFARB, A. AND C. TUCKER (2019): “Digital economics,” *Journal of Economic Literature*, 57, 3–43.
- GROES, F., P. KIRCHER, AND I. MANOVSKII (2015): “The U-shapes of occupational mobility,” *The Review of Economic Studies*, 82, 659–692.
- HERZ, B. AND T. VAN RENS (2020): “Accounting for mismatch unemployment,” *Journal of the European Economic Association*, 18, 1619–1654.
- JÄGER, S., C. ROTH, N. ROUSSILLE, AND B. SCHOEFER (2024): “Worker beliefs about outside options,” *The Quarterly Journal of Economics*, 139, 1505–1556.

- KIRCHER, P. (2022): “Job search in the 21st Century,” *Journal of the European Economic Association*, 20, 2317–2352.
- KUHN, P. AND K. SHEN (2023): “What happens when employers can no longer discriminate in job ads?” *American Economic Review*, 113, 1013–1048.
- LALIVE, R., C. LANDAIS, AND J. ZWEIMÜLLER (2015): “Market externalities of large unemployment insurance extension programs,” *American Economic Review*, 3564–3596.
- LE BARBANCHON, T., L. HENSVIK, AND R. RATHELOT (2023): “How can AI improve search and matching? Evidence from 59 million personalized job recommendations,” SSRN Working Paper No. 4604814.
- LE BARBANCHON, T., J. SCHMIEDER, AND A. WEBER (2024): “Job search, unemployment insurance, and active labor market policies,” Elsevier, vol. 5 of *Handbook of Labor Economics*, 435–580.
- LISE, J., S. SEITZ, AND J. A. SMITH (2004): “Equilibrium policy experiments and the evaluation of social programs,” NBER Working Paper No. 10283.
- MICHAILLAT, P. (2012): “Do matching frictions explain unemployment? Not in bad times,” *American Economic Review*, 102, 1721–50.
- MIGUEL, E. AND M. KREMER (2004): “Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities,” *Econometrica*, 72, 159–217.
- MUELLER, A. I. AND J. SPINNEWIJN (2023): “Expectations data, labor market, and job search,” *Handbook of Economic Expectations*, 677–713.
- MUELLER, A. I., J. SPINNEWIJN, AND G. TOPA (2021): “Job Seekers’ Perceptions and Employment Prospects: Heterogeneity, Duration Dependence, and Bias,” *American Economic Review*, 111, 324–63.
- MURALIDHARAN, K. AND P. NIEHAUS (2017): “Experimentation at scale,” *Journal of Economic Perspectives*, 31, 103–24.
- MURALIDHARAN, K., P. NIEHAUS, AND S. SUKHTANKAR (2023): “General equilibrium effects of (improving) public employment programs: Experimental evidence from India,” *Econometrica*, 91, 1261–1295.
- NAYA, V. A., G. BIED, P. CAILLOU, B. CRÉPON, C. GAILLAC, E. PÉRENNES, AND M. SEBAG (2023): “Designing labor market recommender systems: the importance of job seeker preferences and competition,” *mimeo*.
- NEAL, D. (1999): “The complexity of job mobility among young men,” *Journal of Labor Economics*, 17, 237–261.
- PAPAGEORGIOU, T. (2014): “Learning your comparative advantages,” *Review of Economic Studies*, 81, 1263–1295.
- PATTERSON, C., A. ŞAHİN, G. TOPA, AND G. L. VIOLANTE (2016): “Working hard in the wrong place: A mismatch-based explanation to the UK productivity puzzle,” *European Economic Review*, 84, 42–56.
- PISSARIDES, C. A. (2000): *Equilibrium Unemployment Theory*, MIT press.
- ŞAHİN, A., J. SONG, G. TOPA, AND G. L. VIOLANTE (2014): “Mismatch unemployment,” *American Economic Review*, 104, 3529–64.

- SCHIPROWSKI, A. (2020): “The role of caseworkers in unemployment insurance: Evidence from unplanned absences,” *Journal of Labor Economics*, 38, 1189–1225.
- SPINNEWIJN, J. (2015): “Unemployed but optimistic: Optimal insurance design with biased beliefs,” *Journal of the European Economic Association*, 13, 130–167.
- STAR (2020a): “Dashboard experiment,” Copenhagen: Danish Agency for Labour Market and Recruitment. Statistics Denmark Research Service [distributor]. Accessed September 29, 2020.
- (2020b): “Job search profile data,” Copenhagen: Danish Agency for Labour Market and Recruitment. Statistics Denmark Research Service [distributor]. Accessed September 29, 2020.
- (2020c): “Joblog data,” Copenhagen: Danish Agency for Labour Market and Recruitment. Statistics Denmark Research Service [distributor]. Accessed September 29, 2020.
- (2020d): “Jobnet vacancy data,” Copenhagen: Danish Agency for Labour Market and Recruitment. Statistics Denmark Research Service [distributor]. Accessed September 29, 2020.