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DISCUSSION PAPER SERIES

IZA DP No. 13170

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ABSTRACT

Improving Job Search Skills: A Field Experiment on Online Employment Assistance*

Finding a job requires effective search skills to engage successfully with employers with vacancies. In a field experiment, we test a website that supplements such search skills by providing editable resume and cover letter templates as well as tips on how to look and apply for jobs. Exposure to the website was randomized among about 2,700 job seekers in Australia. The intervention increased job-finding rates, particularly among job seekers aged 35-50 (up to 8 percentage points), with larger effects for women within this age group (up to 10 percentage points). The quality of job matches improved too.

JEL Classification: J08, J64, J68

Keywords: online job search assistance, search skills, active labor market policy

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1 Introduction

Job search assistance (JSA) programs are designed to help the unemployed find a suitable occupation in reasonable time. These programs are a key component of active labor market policy (ALMP), and they traditionally consist of information and assistance services delivered by advisors at employment agencies or job centers. In addition, they typically feature eligibility requirements for the job seekers to receive unemployment benefits, such as proving that they are actively looking for work. Disentangling the effects of the assistance and monitoring components and understanding what kind of assistance can benefit different job seekers are challenging tasks that limit the possibility of tailoring employment services to the needs of the beneficiaries (Crépon and Van Den Berg, 2016; Marinescu, 2017; Card et al., 2018). Recent studies show that low-cost interventions that provide tailored labor market information or information about suitable occupations can improve search behavior and employment outcomes for some job seekers even in the absence of labor-intensive counseling or monitoring (Altmann et al., 2018; Belot et al., 2019). However, poor information is only one of the barriers that job seekers face. Another possible source of search frictions is the lack of job search skills preventing job seekers from engaging effectively with employers with vacancies. For example, a job seeker may be informed about suitable job opportunities and yet lack basic skills to pursue them, such as writing an effective resume or an informative cover letter. Submitting low-quality applications may prevent even motivated and well-informed job seekers from obtaining a job (Thoms et al., 1999), and the question arises of whether helping the unemployed improve such quality can significantly improve their search outcomes.

We address this question by means of a randomized controlled trial that tests the effectiveness of supplementing the assistance provided by job centers with low-cost online resources designed to help job seekers help themselves improve the application process. The experiment was designed and implemented in 2017 in partnership with the then Australian Department of Jobs and Small Business ('the Department', henceforth) and a job service provider, and it involves about 2,700 unemployed workers registered at 22 job centers in Sydney, New South Wales. At a preliminary stage, observing the search behavior of some of these job seekers we realized that many of them were failing to submit tailored, well-written, updated resumes, or did not include cover letters even when required, thus sending a low quality signal at the very first contact with an employer. While staff at job centers can assist in these tasks, it is unreasonable to expect that they would monitor every job application of every job seeker in their caseload. We therefore created a simple self-help website with tailored resources that job seekers would likely find helpful: (i) a resume template and advice on how to customize it; (ii) a cover letter template and advice on how to personalize it; and (iii) tips on how to look and apply for jobs. These materials were developed based on available evidence from the literature and in consultation with staff at the job service provider as well as experts at the Department. Given that the website was developed in-house at the cost of approximately 40 hours of researchers and staff time (alternatively, its development could have been outsourced at a relatively modest cost) and that it required a mere USD20 a month for maintenance, our intervention is both scalable and easy to replicate in other contexts. The 22 job centers involved in the experiment were randomly split into control and treatment centers. The 1,442 unemployed workers registered at the latter were emailed and texted the link to the website. Moreover, job advisors at the 11 treated centers were instructed to mention the website during their regular appointments with job seekers for the duration of the trial (three months), and posters advertising the website were stuck on the walls of treated centers. Neither job advisors nor the 1,248 job seekers registered at the 11 control centers were informed about this online resource.

The outcome of interest in the experiment is an unemployed worker's job-finding rate over time, which is observed for nearly two years since assignment to treatment. Due to a privacy constraint that prevents us from tracking individuals who visited the website, our design allows us to identify average intention-to-treat (ITT) effects. This is the relevant policy parameter given that job seekers cannot be forced to use online resources. Using individual-level administrative data to estimate such effects, we find that exposure to the website increased the job-finding rate of job seekers in the age range 35–50 by about 7 percentage points in the third month from assignment to treatment (off a base of 10.9% in the control group), an effect that persists until the end of the first year (off a base of 27.1%) before slowly converging to about percentage 5 at the end of the observation period

(22 months, off a base of 34.6%). For women in this age group, the average effect is even larger: 9.1 percentage points after three months from assignment to treatment (off a base of 8.1%) and about 10 points from the fourth month to almost the end of the first year (off a base of between 10.8% and 22.1%). The corresponding effects for men are half this size and are never statistically significant. Such gender difference is enough to *revert* the gender gap in the job-finding rate of prime-age unemployed workers. Possible mechanisms that are supported by previous studies include: (i) greater female receptiveness to communication and resources made available during the experiment; and (ii) improved signaling (via a more informative application package) that reduces statistical gender discrimination. Moreover, we detect a positive effect of assignment to treatment on full-time job placements that is again driven by female job seekers and possibly by job seekers aged 34 or younger – a measure of improved quality of job matches (Aaronson and French, 2004; McDonald et al., 2009). At the same time, we also find some evidence of a possible temporary displacement of search effort for job seekers older than 50. For these unemployed workers, the point estimates are systematically negative, which may reflect a reduced ability to make a good use of online employment assistance later in the working life.

These results have implications for the design of JSA programs. Counseling the unemployed is a labor-intensive task that is subject to congestion due to the limited resources of employment agencies. Our findings indicate that low-cost interventions that provide job seekers with basic search tools to engage more effectively with employers, such as a user-friendly website with limited but important resources, can significantly contribute to the speed of exit from unemployment, particularly for prime-age individuals – who may be more motivated to find a job quickly – and women. Some job seekers could be directed to receiving assistance online by default before accessing intensive counseling at a job center. This would also free up resources of frontline staff to provide closer assistance to less digitally savvy job seekers, thus improving the overall cost-effectiveness of JSA. With more citizens around the world being connected online and digitally savvy, these insights are valuable for the improvement of other government services as well.

Our study highlights the importance of basic search skills as a source of labor market frictions and contributes to the evidence on which type of job search assistance is more effective for different types of job seekers. The experimental evidence on ALMP is still limited by institutional constraints that make it difficult to disentangle what works and for whom. For example, the separate evaluation of the counseling versus monitoring components of JSA is still an unresolved issue.[1] Ashenfelter et al. (2005) and Van den Berg and Van der Klaauw (2006) argue that programs focused only on work search verification are not effective, and that JSA may be more beneficial. Crépon et al. (2005) and Hägglund (2007) provide evidence consistent with this suggestion evaluating a set of ALMP in France and in Sweden. Sanders et al. (2019) show that JSA can be improved through administrative simplification.[2] Experimental studies have tested directly the relevance of the lack of information as a cause of search frictions. Because digital technologies allow employment agencies to provide information of increasing quality at a decreasing cost, these interventions can greatly improve JSA programs. In a large-scale field experiment, Altmann et al. (2018) find that an informational brochure about the labor market's state and job search advice helps the long-term unemployed returning to a job. In a different context, Liebman and Luttmer (2015) find that information provision alone can positively alter labor force participation. The authors find that sending an informational brochure and an invitation to a web-tutorial to older workers raised labor force participation by 4 percentage points. More closely related to our study, Belot et al. (2019) implement a low-cost intervention that provides job seekers with targeted occupation advice via a search platform linked to a job vacancies database. The authors show that by broadening their job search, treated job seekers secured more job interviews compared to a control group using the same search platform without targeted advice. The potential of digital technologies and online services was also studied by Stevenson (2009) and Kuhn and Mansour (2014), who document that job seekers using the Internet to find employment are more likely to be employed. More recently, Gürtzgen et al. (2018) find that access to high-speed Internet in Germany improves reemployment rates early in the unemployment spell. Our results suggest that these online tools would be even more effective when complemented by resources that supplement basic job search skills.

[1] A comprehensive meta analyses by Card et al. (2018) cannot separate assistance from sanction programs.

[2] As usual, employment assistance interventions may benefit treated job seekers at the expense of untreated ones, and so there may be little net benefits when general equilibrium effects are considered or when a small-scale intervention is scaled up (Crépon et al., 2013).

2 Experiment design and implementation

2.1 Institutional background

The system of active labor market policy and programs in Australia is called 'jobactive'. In the first place, individuals who are out of work and who wish to receive income support can lodge an allowance claim with the government. The claimers' relative level of labor market disadvantage is then assessed and those who are considered fit to look for work are placed with a job service provider. Providers are compensated by the Department based on measurable outcomes such as job placement and – conditional on a placement – job retention.[3] Jobactive also includes a compliance framework designed to encourage job seekers to engage with their provider, undertake activities to meet their mutual obligation requirements, and demonstrate that they are actively looking for work. One of these activities is regular appointments (usually every other week) with a job advisor at their registered provider center. At their first meeting, job seekers complete a job plan, and the job advisor can determine which programs or services they might be eligible for and benefit from. In subsequent meetings, job advisors can help a job seeker improve their resume and cover letter or enroll them in a training course to learn how to do so.[4] While job seekers must be "work-ready" to enrol with a job service provider, the level of readiness varies. Thus, some job seekers are able to find a job with minimal assistance while others require more guidance. This insight inspired the design of light-touch and easy-to-use resources to help job seekers help themselves improve the quality of job applications.

2.2 Pre-intervention study

These easy-to-use resources were designed based on a combination of best-practice job search techniques – as identified through literature review – and qualitative formative research that we undertook before the trial. Our formative research consisted of: (i) a detailed review of Department desktop resources; (ii) a focus group with ten experienced job coaches from our

[3] More information about Jobactive is available at `https://www.employment.gov.au/jobactive`.

[4] During the trial period, all the control or treatment centers temporarily paused training courses of this type to avoid providing the control group with the resources being tested.

partner provider; (iii) interviews with ten job seekers enrolled with our partner.[5] Such casual observation suggested that many job seekers were submitting low quality job applications, for example resumes that were not updated or tailored to the vacancy they were applying for, or not attaching cover letters even when required. A variety of reasons explain this behavior, including low awareness of the requirements of job applications, poor feedback from previous applications, perceptions that writing more would make a negative impression due to low literacy levels, and low motivation levels after repeated failures to secure an interview. These suggestions were backed up by the Department's employer survey data, which indicate that one in five employers reported not interviewing applicants because their written application was not tailored to the position, failed to address selection criteria or had spelling mistakes (DJSB, 2015). In the same survey, employers reported placing a large emphasis on the applicants' communication skills, which one's application package typically reveal. Details such as attaching a cover letter, reporting in one's resume up-to-date and clear professional contact details, work experience, job responsibilities, qualifications and certifications, achievements, and professional objectives have been shown to be important across a number of industries (Hornsby and Smith, 1995). In addition to grammatical errors, certain pieces of information are instead better avoided, such as high school education – unless it is the most recent – or demographic details such as age, marital status, and parental status (Schramm and Dortch, 1991; Toth, 1993; Thoms et al., 1999; Ross and Young, 2005). Since one's resume and cover letter are the first opportunity to demonstrate communication skills, job seekers who are unaware of these guidelines miss out on leaving a good first impression and send a negative signal about their qualities to a potential employer.

A similar pattern emerged for job search strategies. Some job seekers did not use free online job search platforms, some appeared to inefficiently trade-off application quality for quantity, and others applied repeatedly to the same employer despite previous rejections, not expanding their job search geographically or by industry. While it is part of the responsibilities of job advisors to support job seekers with job search resources and strategies, it is often

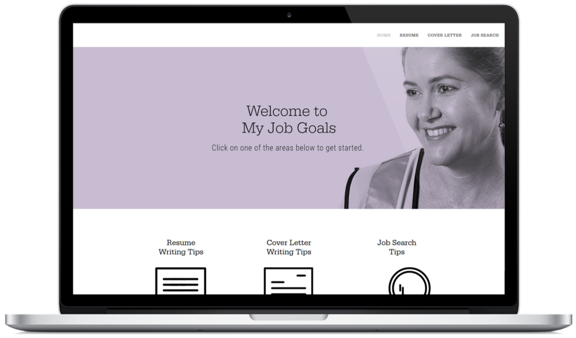
[5] In order to avoid disruption, we acted as mere observers of job seekers–staff interactions during their regular appointments, and we talked informally to some of these job seekers after these meetings. Due to privacy reasons, we were not able to assess the materials that job seekers used to apply for jobs, which is why we complemented it with a desktop research.

difficult to provide tailored assistance due to multiple job seekers requiring attention at the same time and other administrative responsibilities. Moreover, job advisors can persuade job seekers to improve their job search behavior, but close monitoring of every application for every assisted person is not feasible.

2.3 Intervention resources

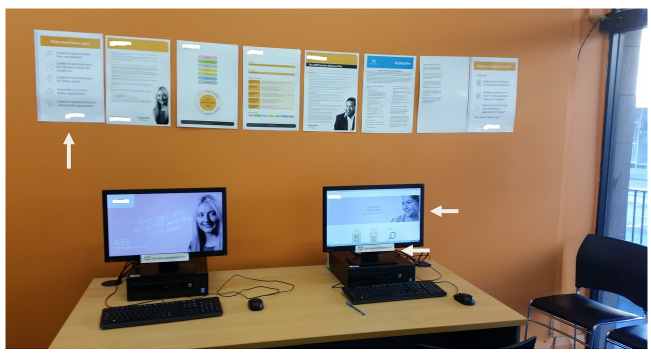
The picture emerging from this preliminary study was thus one of poor job search skills, possibly for a substantial fraction of job seekers. To supplement these skills, we designed a resume and cover letter templates that contain all the right features described above and we compiled evidence-based job search strategies into a short checklist containing ten tips to follow when pursuing vacancies. We then set up to make these three key job search resources available online, on a purposely designed website that would be accessible both at job centers and at job seekers' homes. These resources are reproduced in the Online Appendix. The website was called 'My Job Goals' (MJG) and, as illustrated in Figure 1, it was designed to be straightforward and self-explanatory: the homepage had clear and visible links to three webpages, each focused on one of the resources described above. Each webpage contained a brief explanation on the importance of the resource for job seeking, and a downloadable template in MS Word for the resume and cover letter. To reinforce further the value of the webpage content, each page had a short video explanation from an experienced staff member of the job service provider. The style of the website, including colors, photos, and fonts, purposely resembled the marketing and communication material of the job service provider. The logo of the provider was also clearly visible at the top of the homepage and each webpage to ensure familiarity and trust with the source of the communication. Figure 2 shows how MJG was accessible at one of the treated job centers' search facilities. Posters advertising the website are also visible in this picture. The rationale for providing these resources online was threefold: first, we wanted to test solutions that were replicable and scalable at low-cost; second, relax the time constraint of frontline staff at job centers; third, help job seekers to focus on their online job application process. Given the increasing importance of online platforms to look and apply for jobs, offering online assistance supports job seekers in an environment that is best suited to their needs.

Figure 1: The 'My Job Goals' website



Notes: The figure shows the homepage of the 'My Job Goals' (MJG) website, an online resource designed for the experiment and containing editable resume and cover letter templates and a checklist with tips on how to look and apply for jobs. The website was accessible to job seekers both at job centers and at home between May and August 2017. The logo of the provider was clearly visible at the top-left of the screen on each page, but was removed from this picture for confidentiality reasons.

Figure 2: Accessing 'My Job Goals' at a provider's facility



Notes: The figure shows how 'My Job Goals' (MJG) was accessible at one of such facilities. A posters advertising the website is also visible in this picture. The logo of the provider was removed from this picture for confidentiality reasons.

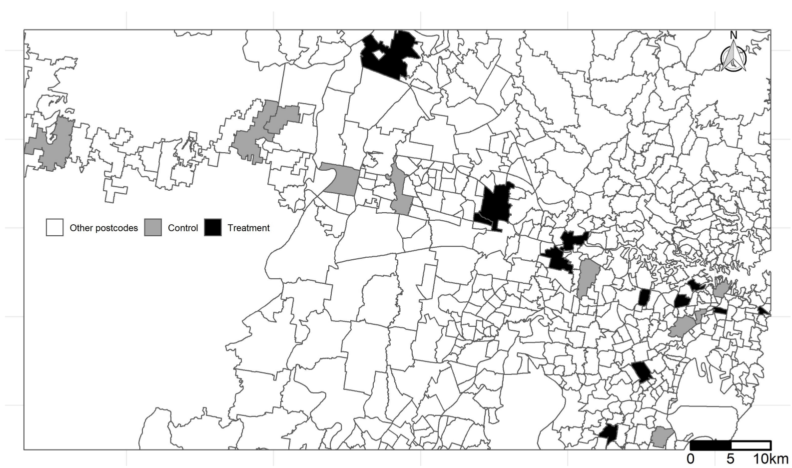
2.4 Randomized trial design

In partnership with the Department, we sent a call for expression of interest to all Jobactive providers. Among those that responded, we prioritized larger providers which had the capacity to work with the research team for a randomized trial in Sydney, New South Wales. There are many such providers in the system, which are similar in terms of Jobactive metrics.[6] A field experiment that randomized the provision of information about MJG was then conducted between May 15 and August 15, 2017. In order to minimize spillovers onto job

[6]The Jobactive star rating system is a tool to evaluate providers' performance in terms of placement and job retention. The Department issues a report every quarter. All reports are available at www.employment.gov.au/jobactive-star-ratings-and-performance.

seekers in the control group (and because crucial aspects of the trial such as the presence of posters and the role of job advisors cannot be varied within job centers) the randomization was conducted at the level of job centers. The selected provider had 22 centers in Sydney, which we randomly assigned to treatment and to control. Job seekers who, at the beginning of the trial, were registered at the provider's job centers that were assigned to treatment constitute the treatment group, which is a total of 1,442 persons. The control group is given by 1,248 job seekers who, at that same date, were registered at the provider's job centers that were assigned to control.[7] The Online Appendix provides more details on the randomization strategy that was adopted. This experimental design is such that both the sampling process and the assignment mechanism are clustered at the job center level, which requires adjusting standard errors appropriately (Abadie et al., 2017). We return on this issue in what follows. Figure 3 shows the spatial location of treated and control centers in the Sydney metropolitan area. Table 1 summarizes and compares the observable pre-treatment characteristics of the two groups. The randomization balanced virtually all of these, thus boosting the credibility of the control group as a valid counterfactual for treated job seekers.[8]

Figure 3: Spatial location of job centers assigned to treatment or to the control group



Notes: The figure shows a map of postcode areas in the metropolitan area of Sydney, NSW. The postcodes containing the 11 job centers assigned to treatment and the 11 job centers acting as control centers are filled in black and in gray, respectively.

[7]We do not consider 1,039 job seekers who registered at the provider's job centers during the trial, i.e., between May 16 and August 15, 2017 (541 at treated job centers and 498 at control ones).

[8]As usual, the possible effects of the few imbalances in a finite sample can be eliminated by using these pre-treatment covariates as conditioning variables when regressing the outcome on the treatment indicator.

Table 1: Characteristics of job seekers in treatment and control groups

Variable	Controls		Treated		p-value
Female	0.497	(0.500)	0.469	(0.499)	0.147
Age	39.98	(13.00)	39.89	(12.77)	0.862
College degree	0.142	(0.349)	0.144	(0.351)	0.899
Vocational degree	0.254	(0.435)	0.252	(0.435)	0.925
High School degree	0.238	(0.426)	0.241	(0.428)	0.872
Less than high school	0.240	(0.427)	0.243	(0.429)	0.850
Missing education information	0.010	(0.098)	0.004	(0.064)	0.084
Aboriginal/Torres Strait Islander	0.076	(0.265)	0.077	(0.267)	0.934
People with disability	0.325	(0.468)	0.326	(0.469)	0.938
Primary caregiver	0.127	(0.334)	0.135	(0.342)	0.550
Homeless	0.089	(0.286)	0.109	(0.312)	0.099
Ex-offender	0.097	(0.296)	0.113	(0.317)	0.176
Worked in pre-intervention year	0.260	(0.439)	0.271	(0.445)	0.500
Mobile phone number available	0.947	(0.222)	0.952	(0.212)	0.557
E-mail address available	0.385	(0.487)	0.357	(0.479)	0.130
N	1,248		1,442		

Notes: The table reports the means and, in parentheses, the standard deviations of observable pre-treatment characteristics of job seekers in the treatment and control groups. The p-value in the last column refers to a t-test of the null hypothesis that the means are equal across the two groups.

Job seekers in the treatment group were directed to the website via digital and in-person channels. The digital channel consisted of text and email messages, sent only once (on the trial launch date) to the job seeker's mobile number and email address present in the Department's database. Not all job seekers had a valid mobile number or email address in the database. Valid phone numbers were available for 85% of treated job seekers but, as explained in more detail in the Online Appendix, only 26% of them had a valid email addresses. We don't know how many job seekers opened the website from the link reported in the SMS (although the website metrics reported in the Online Appendix provide an indirect measure) but we know that 32% of those who received the email opened it and, of these, about 25% clicked on the link to the website. To these one must add any other untraceable visit, such as those made by one of the PCs of the job centers.

The in-person channel consisted of cues in job centers, including posters that we designed and hung in visible spots on the walls of treated job centers (see Figure 2), and communication by job advisors. We visited the treated sites a few days before the trial launch date to instruct job advisors on how to explain the benefits of the websites to job seekers during their regular appointments. To facilitate this work, we provided the job center staff with a one-page document that they could consult if needed. During these visits we also hung the posters and a strip of paper underneath the job center PC screen with the website URL. The posters and job advisors' cheat sheet are reproduced in the Online Appendix.

On the trial end date we shut down the MJG website and physically removed the posters and any other material from the treatment sites. Detailed website metrics are reported in the Online Appendix. These indicate that the website was visited 1,659 times during the trial period. Traffic to the site peaked when SMS and email messages were sent out at the beginning of the trial. The resume and cover letter template pages were visited by 424 and 260 unique individuals, respectively, for about 2 minutes each on average. This is enough time to inspect the document and download it. The job search tips page was visited by 359 unique visitors, for 2.6 minutes on average. Due to privacy regulations, we could not track the identity of those job seekers who visited the website or downloaded material from it. As a consequence, we can only identify the intention-to-treat (ITT) effect, i.e., the effect on job-finding of being invited to use MJG via the digital and in-person channels. This is the estimand that we target. It is also the relevant parameter from a policy perspective given that the employment agency cannot force job seekers to use online resources.

We cannot exclude that there was some contamination between treatment and control groups during the trial. The website was freely accessible on the Internet and so job seekers in the control group may have accessed it. For example, they may have heard about it from other job seekers they know, or they may have seen the posters by walking into job centers assigned to the treatment group (although the spatial distribution of treatment and control centers shown in Figure 3 makes contamination less likely). Similarly, job advisors at treated centers may have appreciated the website resources and they may have shared them with their colleagues at control centers. However, in our context noncompliance is one sided under the assumption that treated job seekers do not ignore the information they receive. Therefore, the possible violation of SUTVA in our experiment results, at worst, into attenuation bias in the estimated ITT causal effect.

3 Results

The outcome of interest is whether a job seeker left the unemployment state at least once by a certain date,[9] which is observed from administrative data maintained by the Department for nearly two years since the beginning of the trial. We consider only job placements secured by the job seeker directly (which we label "self-found"), i.e., not from a vacancy originally secured by the job service provider. This notion of job finding is of primary interest in our evaluation because the aim of MJG is precisely to help job seekers help themselves without a direct, specific intervention of the job center in the finalization of the placement. Following a placement, it is a job advisor's responsibility to register it as self-found or provider-sourced by simply ticking a box in the administrative software. This does not affect the monetary compensation or evaluation of either the provider or the job advisor because a job seeker may have of course benefited from the broad support provided by the job center in finding her or his own job. About 90% of job matches in our data are of the self-found type.

3.1 Duration analysis

We begin our causal analysis by constructing Kaplan-Meier failure functions for eight demographic groups that are of interest in consideration of their relevance in the ALMP literature. These functions are reported in Figure 4. The "failure" is the event of leaving unemployment thanks to a self-found job, and the outcome is censored at the last date of data extraction from the Department databases (February 5, 2019). The first date a "failure" can be observed is May 15, 2017. Given the randomized design, the failure function for the control group can be interpreted as the counterfactual job-finding rate that treated job seekers would have experience in the absence of MJG at any point in time. About 5% of all job seekers in the control group are matched within one month, about 10% within two months, and about 13% within three months. After six months, about 22% have obtained at least one job match, about 29% after one year, and about 36% after twenty-two months. A small, positive difference between the job-finding rates of treated and control job seekers emerges

[9] It is possible that a job match is realized and subsequently destroyed. The employment state of a job seeker who left Jobactive is not directly observable in the Department data.

after the second month. Such a difference is appreciably larger among job seekers between 35 and 50 years of age (possibly negative in the early months since assignment to treatment for older job seekers and after fifteen months for younger ones), especially women. For these women in the age range 35-50, the gap between the two failure functions is comparable to the gender gap in the job-finding rate that we observe after two months at the baseline. We comment below on this notable fact. We next reproduce these non-parametric differences in a regression framework to better quantify their magnitude and statistical significance.

3.2 Regression analysis: baseline results

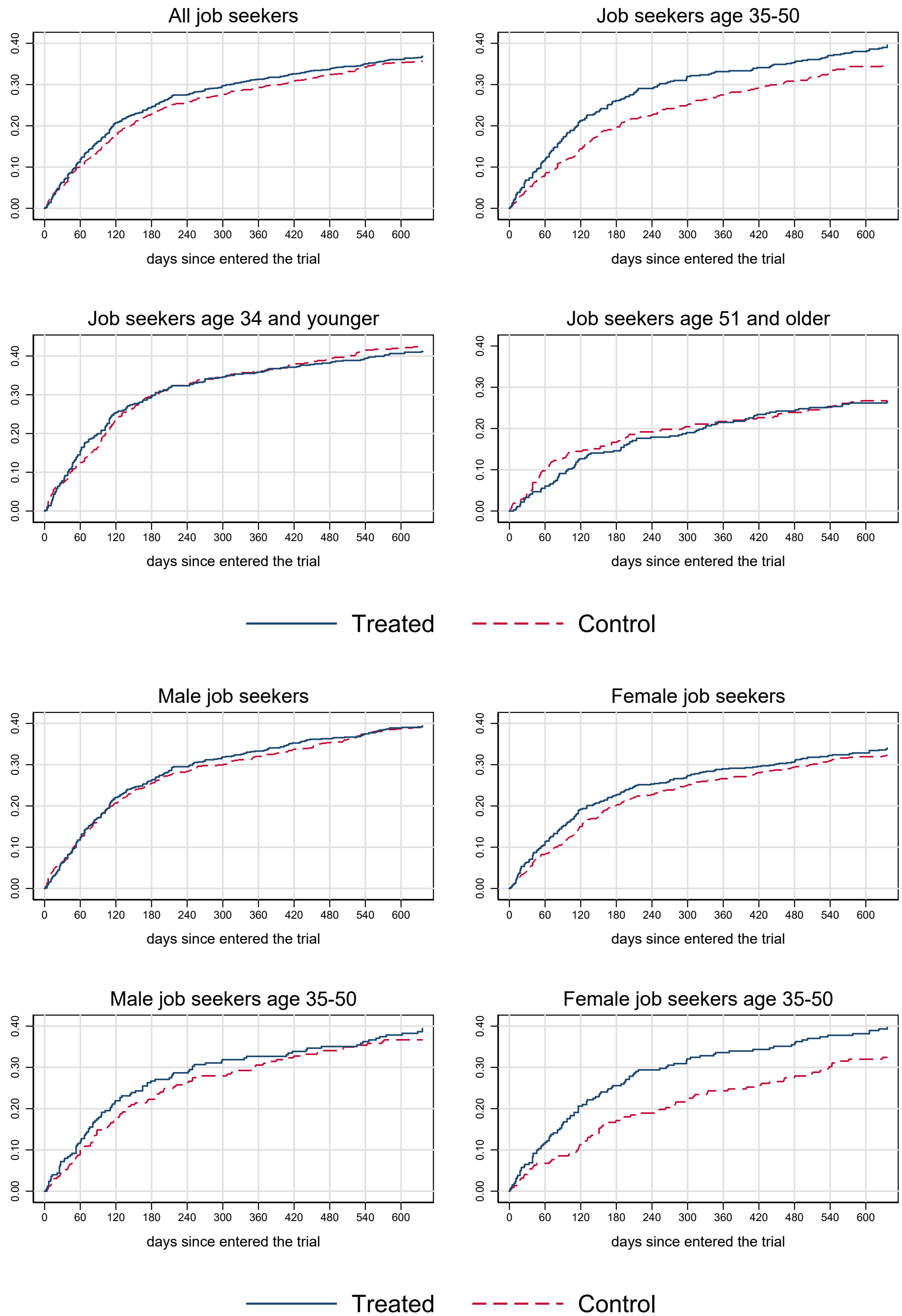
We estimate by OLS linear models of the type

$$Y_{im} = \alpha_m + \beta_m D_i + \gamma_m X_i + \epsilon_{im} \tag{1}$$

for each month $m = 1, 2, \cdots, 22$ since job seeker i entered the trial. In the baseline specification, Y_{im} is a binary variable indicating whether, by month m into the trial, i obtained a job match of the self-found type. In all specifications, D_i is a dummy indicating whether at the start of the trial job seeker i is registered with a job center assigned to treatment, and vector X_i contains the covariates summarized in Table 1. Therefore, parameter β_m identifies the average ITT effect after m months. This is the causal, policy-relevant parameter that we estimate. We also have data on any job matches in the year preceding the intervention, which we use to estimate equation (1) also for lagged $m = -1, -2, \cdots, -12$. The resulting estimates provide a placebo test because β_m should be zero at all these pre-trial lags.

Our experimental design features clustering at the level of job centers both in the sampling process and in the assignment mechanism, which requires to adjust standard errors for clustering of unobserved shocks at this same level (Abadie et al., 2017). However, with only 22 job centers in the sample we are subject to the perils of clustering in the presence of few clusters (Cameron and Miller, 2015). We resolve this tension by, first, applying the wild cluster bootstrap (Cameron et al., 2008) and then conservatively selecting the confidence interval associated with the largest between the p-value from a test of $H_0 : \beta_m = 0$ produced by the bootstrapping procedure (which accounts for clustering at the job center level) and the conventional one (which is robust to general heteroskedasticity only).

Figure 4: Cumulative job-finding rates by treatment status



Notes: The figure shows Kaplan-Meier failure functions by treatment status. The horizontal axis measures the number of days since entering the trial, and the "failure" is the event of leaving the unemployment state thanks to a self-found job.

This empirical methodology produces 34 point estimates of β_m and their confidence intervals, which can be conveniently reported in a graph (the Online Appendix contains the associated tables and p-values). Figure 5 shows such points estimates (dots) for eight groups defined by age and gender when the outcome is any self-found job match, as well as the 95% confidence interval (caps). In the pooled sample of all job seekers (top-left panel), exposure to MJG causes a marginally significant increase in the job-finding rate of 3.5 percentage points (p-value = 0.053) in the third month since entering the trial. Subsequently, job seekers in the control group slowly catch up with their treated counterparts and so this point estimates reverts to the pre-treatment value after about eighteen months. As expected, all point estimates are zero in the year preceding treatment.

This small average effect masks important heterogeneity, as revealed by the remaining panels of Figure 5. First, the effect is much larger for job seekers between 35 and 50 years of age. For these individuals in the middle of prime-age, exposure to the website induces a job-finding rate that by the third month from assignment to treatment significantly exceeds the one for the control group by 6.9 percentage points. This effect increases to between 7 and 8 percentage points between the fourth and the eleventh month and then slowly declines and converges to a statistically insignificant 4 percentage points. The finding that the effect is driven by job seekers in the age range 35-50 is consistent with the results by Card et al. (2018), who report smaller average effects of ALMP for older workers and youth.

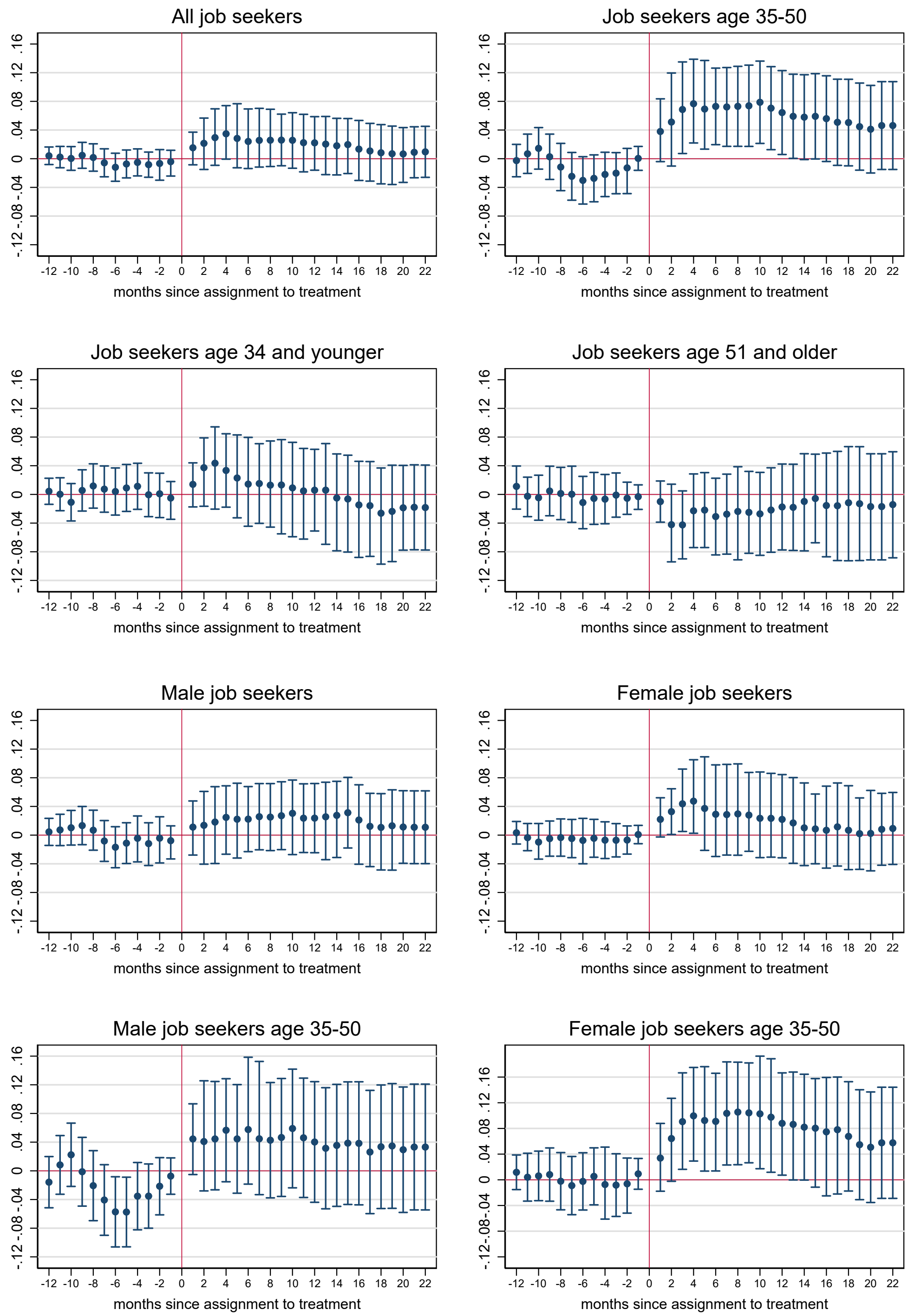
Second, in this age group 35–50, the average ITT is substantially larger for female job seekers than for males. For men the average effect is about 4–5 percentage points in the first year – although never statistically significant – converging to about 3 percentage points thereafter. For women, instead, this effect is twice as large and significant, 9–10 percentage points from the third month and throughout the first year from the intervention, slowly converging to an insignificant 6 percentage points afterwards. This is a large effect considering that in Figure 4 between three months and one year from entering the trial the job-finding rate for women 35 to 50 years of age in the control group ranges between about 8% and 24%, and that it is little above 32% after 22 months. The gender heterogeneity in the average ITT that we estimate *reverses* the gender gap in the job-finding rate in the absence of the intervention that is visible in Figure 4: for men aged 35–50, the job-finding rate in the control group between three months and one year from entering the trial ranges between 14% and 30%, and it is nearly 37% at the end of the observation period. Thus, exposure to MJG is particularly beneficial to prime-age women. This finding too is consistent with Card et al. (2018), who report larger impacts of ALMP for women. A possible explanation in our context is that the resources available at the website helped women improve the quality of their job applications by making their package more informative to employers. For example, in a set of experiments, Exley and Kessler (2019) find significant differences in self-promotion between men and women. These authors suggest that women have internalized that self-promotion is inappropriate or risky. The standardized job search material provided via MJG may have attenuated the gender gap in signaling skills to employers. Another possible explanation is that women are more receptive than men to the resources made available by the experimenter (communication material and job coaches' advice about MJG, in our case), as suggested in different contexts by Eckel and Grossman (2008) and Angrist et al. (2009).

Third, there is some evidence that the ITT effect may be temporarily negative for unemployed workers older than 50. For them, exposure to the website reduced the probability of finding a job by 4.2 percentage points by the third month from assignment to treatment (p-value = 0.079). Afterwards, this point estimates slowly reverts towards zero. Although in this case we lack the statistical precision to reach reliable conclusions, a possible explanation is that the intervention induces older workers to use new job search tools and methods through a digital platform they may have a harder time becoming familiar with.[10] This possible displacement effect for older workers is noteworthy given that our intervention aimed at complementing existing in-person assistance service by job advisors, not replacing them.

We remark that this pattern is robust to using the broadest notion of job finding available in our data, namely whether there is a placement regardless of whether this is of the self-found type or not. In this case the confidence intervals become larger but the overall pattern produced by the point estimates is unchanged.

[10]The Australian Bureau of Statistics reports that in 2017, 98% of individuals aged 18-34 used the Internet regularly, followed by 94% of those aged 35-54, while a much lower 69% for those aged 55 or more.

Figure 5: Results: all self-found jobs



Notes: The figure shows, for each month since entering the trial (positive values on the x-axis) and for the 12 months preceding the trial (negative values on the x-axis), the estimated average intention-to-treat effect (parameter β_m in equation 1), represented by a circle. The outcome Y_{im} is a dummy taking value 1 if by month m into the trial (values on the x-axis) jobseeker i obtained *any* job in a way classified by the job center as "Found Own Employment" (self-found) and 0 otherwise. The figures also shows the associated 95% CI associated with the largest between the p-value from a test of $H_0 : \beta_m = 0$ produced by the wild cluster bootstrap (clustering at the job center level) and the p-value implied by heteroskedasticity-robust standard errors.

3.3 Quality of job matches

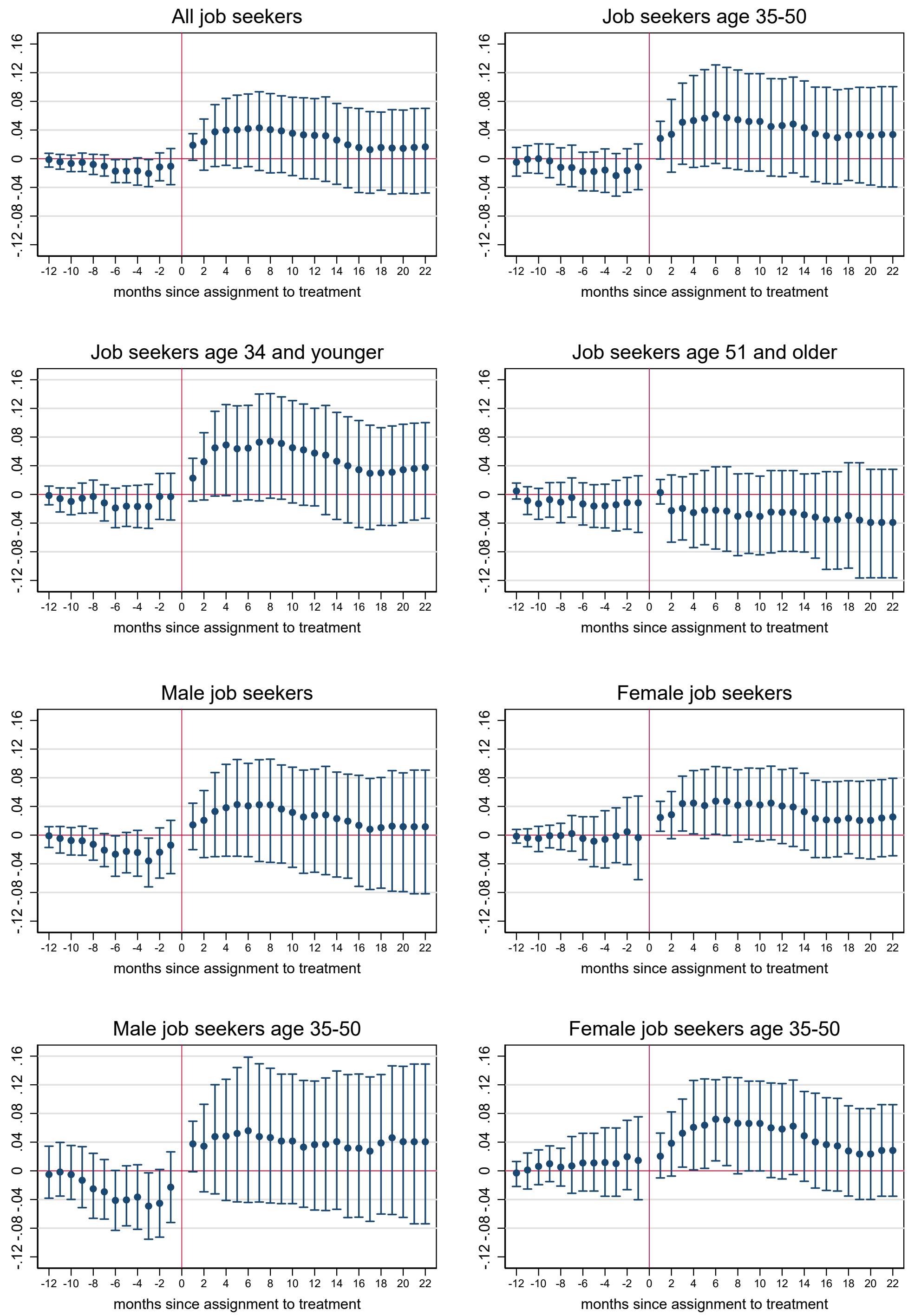
We next replicate the analysis using a more stringent notion of job finding to assess the intervention along other dimensions. We first consider matches with full-time jobs, which can be regarded as jobs of higher quality relative to part-time ones. For example, Aaronson and French (2004) document the existence of a wage penalty for part-time jobs (concentrated on men), and McDonald et al. (2009) uncover – although in a small sample – a similar penalty for responsibilities, careers, and work intensity (borne mostly by women). Figure 6 shows that when pooling all job seekers (top-left panel), the average ITT effect on the transition rate from unemployment to a full-time job is positive and marginally significant after the first month from entering the trial (about 2 percentage points), increasing to about 4 percentage points (not statistically significant) for the entire first year, before reverting to the pre-intervention level of zero. Among women in the age group 35-50, this effect is statistically significant between the third and tenth month from assignment to treatment, and peaks after six months (nearly 8 percentage points).

Next, consider job matches that, retrospectively, will last for at least 6 months. These more stable jobs are the hardest to secure for a job seeker at the baseline: after one year since entering the trial, only 15.6% of job seekers in the control group obtained a placement in such jobs, as opposed to 30% in any job. Figure 7 shows that in this case no significant ITT effects are detected. Nonetheless, the intervention may have helped securing temporary job placements that could provide a springboard for future, more stable, employment (Booth et al., 2003; Ichino et al., 2008).

3.4 Post-trial survey

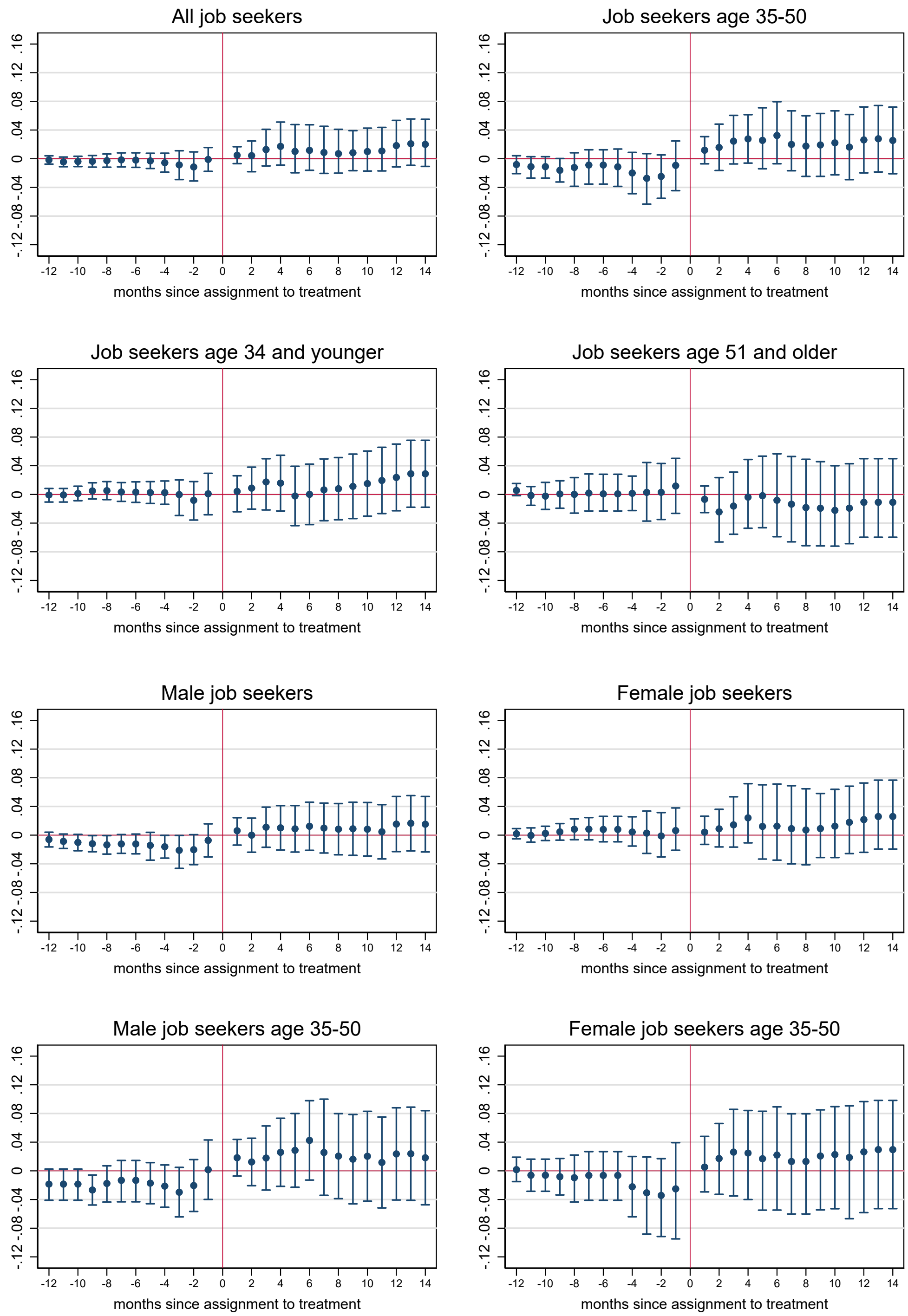
As part of the evaluation of the trial, an anonymous online survey of a random sample of 127 job seekers was conducted after the end of the experiment. The participation rate was 96%. Given the focus of the trial on online assistance, one question concerned the need for support and the way to receive it. Of the 40% who said they wanted more job search support, 80% said that they would be happy to receive such support from a website. The remaining 20% said they would prefer face-to-face interaction when receiving job search help.

Figure 6: Results: full-time self-found jobs



Notes: The figure shows, for each month since entering the trial (positive values on the x-axis) and for the 12 months preceding the trial (negative values on the x-axis), the estimated average intention-to-treat effect (parameter β_m in equation 1), represented by a circle. The outcome Y_{im} is a dummy taking value 1 if by month m into the trial (values on the x-axis) jobseeker i obtained a *full-time* job in a way classified by the job center as "Found Own Employment" (self-found) and 0 otherwise. The figures also shows the associated 95% CI associated with the largest between the p-value from a test of $H_0 : \beta_m = 0$ produced by the wild cluster bootstrap (clustering at the job center level) and the p-value implied by heteroskedasticity-robust standard errors.

Figure 7: Results: self-found jobs kept for at least six months



Notes: The figure shows, for each month since entering the trial (positive values on the x-axis) and for the 12 months preceding the trial (negative values on the x-axis), the estimated average intention-to-treat effect (parameter β_m in equation 1), represented by a circle. The outcome Y_{im} is a dummy taking value 1 if by month m into the trial (values on the x-axis) jobseeker i obtained a job in a way classified by the job center as "Found Own Employment" (self-found) *that was kept for at least six months* and 0 otherwise. The figures also shows the associated 95% CI associated with the largest between the p-value from a test of $H_0 : \beta_m = 0$ produced by the wild cluster bootstrap (clustering at the job center level) and the p-value implied by heteroskedasticity-robust standard errors.

The vast majority (90%) of job seekers looked for jobs online, 30% in the newspaper, 20% were referred to jobs by their job advisor, and 19% looked on community noticeboards. Job seekers were also asked to use a self-efficacy scale to report their perceived quality of life and any difficulties they faced in looking for a job. Respondents reported feeling confident about most aspects of the job search process. When asked what their main barriers to employment were, they reported: lack of experience or gap in employment history; discrimination; geographical issues; and mental health issues.

Other questions were about application material. A cover letter was used by 70% of respondents, and 67% of these said they attached it to each job application. Reasons job seekers did not have a cover letter included: the job application did not specify that one was needed; the job seeker perceived that it was not important; it was time consuming; they did not know how to write one. The majority of job seekers reported updating their resumes within the last month, with 70% of them reporting modifying their resume when sending it out as part of a job application. Those who indicated that they did not update their resume reported that it was either not worthwhile doing so, or it was not necessary since all the jobs they applied for were similar.

Finally, job seekers were asked whether they had contact with the MJG website and what resources they accessed. It is not possible to reliably assess the number of surveyed job seekers who had contact with the MJG website and where they saw it because many of them seemed to have misunderstood the question as asking whether they had used the general provider website (this was evidenced by saying they had been referred to it by another government website or Google). This makes it difficult to determine how reliable job seeker's feedback on the trial resources were. Regardless, job search tips were rated highest, followed by resume support and cover letters.

4 Conclusions

Unemployed workers may struggle to secure a job not only due to the lack of information but also because of poor job search skills leading to low-quality applications. The field experiment studied in this paper shows that the low-cost online provision of user-friendly and easy-to-access tools to submit job applications of improved quality may speed up exit from unemployment, an advantage that for some job seekers – most notably those aged 35-50 and in particular women in this age group – may persist for more than a year and involves full-time jobs.

The usual caveats concerning randomized trials that test new policies apply to our experiment. It is possible that a scaled-up intervention would trigger general equilibrium effects that would alter our conclusions. Moreover, what works in Sydney may not necessarily work in other contexts (although our trial covers a geographical area that goes beyond the Sydney city center, including locations that are more than 40 miles from the economic hub of the city). Another special feature of our intervention is that it was implemented in Australia, a country with almost full high-speed Internet penetration. One could argue that in countries where geographical remoteness is associated with poorer broadband infrastructure the effect would be weaker. An outstanding question that we cannot answer in this paper is whether online assistance – not just of employment services – is a complement or a substitute for more traditional forms of in-person services. Job seekers in our experiment could not be exempted from the legislated compulsory regular appointments with their job advisors, which implies that we could not allocate a treatment group to receive online assistance alone. If online and in-person assistance are complements or substitutes in producing job offers then our randomized trial cannot, per se, isolate the effect of online resources. Similarly, we cannot disentangle which of the online tools we used worked and which, if any, did not. Finally, it is possible that part of the effects that we identify are generated not by exposure to MJG but by other inputs (such as reminders to look for work or nudges from the job advisor) that implicitly come with the digital and in-person referral to MJG for those job seekers who were assigned to treatment.

Despite these limitations, to the best of our knowledge this is the first study that provides experimental evidence from the field on providing employment assistance online, thus complementing previous experiments testing low-cost interventions to improve job search behavior (Altmann et al., 2018; Belot et al., 2019). The potential of online assistance is not limited to job search. For example, Jackson and Makarin (2018) show that teachers can greatly benefit from the availability of key teaching resources from the Internet. Such potential is particularly relevant for public services. Future generations in advanced economies will expect government services to be easily accessible online, and a better understanding of the pros and cons of these new tools is useful to inform policy. One of the advantages of offering public services online is the possibility to evaluate them with minimal resources, leveraging on a wealth of administrative data to improve these services while reducing their costs. This can improve our understanding of what works and what doesn't and also for whom it may work, moving beyond average effects. Furthermore, the allocation of government programs and services is often based on preset eligibility criteria. However, the information available at the time of enrollment in a program is often limited, leading to defaulting citizens into services that may offer little or no value to them, thus affecting the success of a program. At the same time, researchers can look more closely into how eligibility criteria affect program success. In our study we were able to measure the impact of our intervention on different age and gender groups, despite these characteristics not being crucial eligibility criteria in active labor market policies. The present study reinforces the case for online government assistance services as a promising avenue for both researchers and policymakers.

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