Encouraging and directing job search: direct and spillover effects in a large scale experiment.*

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Preliminary, December 2, 2022

Abstract

We analyze the employment effects of directing job seekers' applications towards establishments likely to recruit, building upon an existing Internet platform developed by the French public employment service. Our two-sided randomization design, with about 1.2 million job seekers and 100,000 establishments, allows us to precisely measure the effects of the recommender system at hand. Our randomized encouragement to use the system induces a 2% increase in job finding rates among women. This effect is due to an activation effect (increased search effort, stronger for women than men), but also to a targeting effect by which treated men and women were more likely to be hired by the firms that were specifically recommended to them.

In a second step, we analyze whether these partial equilibrium effects translate into positive effects on aggregate employment. Drawing on the recent literature on the econometrics of interference effects, we estimate that by redirecting the search effort of some job seekers outside their initial job market, we reduced congestion in slack markets. Estimates suggest that this effect is only partly offset by the increased competition in initially tight markets, so that the intervention increases aggregate job finding rates.

*We thank Pôle emploi and La Bonne Boîte for their support throughout the project; funding by EUR grant ANR-17-EURE-0001 is acknowledged. We thank Faustin Schneider and Anna Carrere for invaluable research assistance. We thank Philippe Aghion, Axelle Ferrière, Dylan Glover, Thomas Le Barbanchon, Philipp Kircher, David Margolis, Paul Müller, Roland Rathelot, Alexandra Roulet, Gilles Saint-Paul, and numerous seminar participants at Bocconi university, Centre d'analyse et de mathématique sociales (CAMS-EHESS), Collège de France, European University Institute (Florence), INSEAD, PSE, Tinbergen Institute, and the 2020 "Matching jobs and workers onlin" IZA workshop. All remaining errors are ours. The views expressed in this paper do not reflect the views of the Banque de France.

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I Introduction

The commercial success of several private recommender systems — Internet-based platforms that go beyond posting job ads or applicant profiles by providing targeted recommendations on potential matches — shows that these services meet a demand on both sides of the labor market, suggesting that they yield positive private returns to firms and job seekers.[1] Can recommendation algorithms be leveraged beyond these private benefits, in order to increase social welfare by reducing search frictions and increasing aggregate employment? Hypothesizing a positive answer, public employment services (PES) have shown increasing interest in providing targeted recommendations, either as an add-on to their main job ads platform, or as separate services. Specifically, based on their profile (if they are logged in) or simply on their actions on the platform, job seekers receive recommendations to expand their search to neighboring occupations, or to apply to specific firms to which they might not have spontaneously applied.

The rationale is that such services may increase equilibrium employment by reducing the cost of search frictions, through two distinct mechanisms: a reduction in individual job seekers' or firms' search cost, and a reduction in occupational mismatch if the platform's recommendations to job seekers are targeted toward tighter occupations. In practice, this simple theory of change may however be questioned for two related reasons. First, to reduce informational frictions, the PES' advice needs to be based on better information than privately available to job seekers and firms. If not, irrelevant recommendations may actually increase search cost as they push job seekers to apply where they would not be productive, in turn overwhelming firms with bad candidates and increasing their screening costs. In that respect, the PES' informational advantage likely lies in the administrative data it has on the supply and demand of labor at the local level. This allows to identify local mismatches that may not be visible to individual players. However, here comes the second difficulty: to leverage its informational advantage, the PES needs to trade off occupational mobility costs against congestion externalities. Indeed, recommending the job seekers to broaden their search toward a tighter nearby occupation may help by reducing congestion effects, but it also imposes a mobility cost (adjust their skills to a different job, or working in a second-choice occupation). How far one should recommend job seekers to go is not obvious. To sum up, in order to reduce frictional unemployment, public recommendation algorithms must find reliable operational solutions on two fronts: gather reliable local tightness measures, and parameterize the algorithm so as to reduce mismatch without inducing excessive mobility costs.

In this paper, we provide experimental evidence on the potential social value of a large-scale public recommendation algorithm developed by the French public employment service. The platform is called "La Bonne Boîte" ("The adequate firm," henceforth LBB). It was started in

[1] See in particularHorton (2017); Kuhn and Skuterud (2004); Kuhn and Mansour (2013); Kuhn (2014); Belot et al. (2018b,a) for studies of job search platform / recommender systems. Kircher (2020) provides a recent review of this literature.

2015, based on an algorithm predicting hirings at the firm $\times$ occupation level. The goal of the PES with this service is to provide job seekers with access to the so-called “hidden market” of firms that recruit without necessarily posting job ads. On the business-as-usual mode, the LBB website directs job seekers toward a list of firms most likely to hire them according to the location and occupation criteria they enter. We partner with the PES to test the impact of this service using a randomized encouragement design: we send emails to about 800,000 registered job seekers (the treatment group) to encourage them to use LBB, and measure the impact on job finding rates. To analyze mechanisms and potential improvements, we use the encouragement emails sent to treated job seekers one step further, in the form of targeted recommendations toward specific firms within and outside their occupation of reference. While we introduce some random variation when making these recommendations, we also discipline ourselves using a simple, flexible equilibrium model at the commuting zone level. The model takes into account information on local tightness across occupations and makes educated guesses on key parameters (occupational mobility costs, firms' screening technology) to optimize recommendations in order to maximize the expected local aggregate employment. In a second step, we analyze ex post whether these presumed optimal recommendations were indeed effective. Specifically, we ask two questions : (i) Is there a positive private return to the email's recommendations and encouragement to search via LBB? This is directly identified by the reduced form effect comparing treated job seekers (who received the email) to control ones (who received no email). (ii) Do the recommendations generated by the ex ante model strike the right balance, in terms of the breadth of occupational search, between congestion and mobility costs? Answering this second question is harder, as it involves estimating interference effects: recommendations made to a given job seeker, if they lead to a change in their application behavior, are likely to have external effects by displacing other job seekers. We build upon the recent literature on interference in randomized trials, in particular Hu et al. (2022), to estimate not only the direct effect but also the indirect effect of recommendations.

We find that the e-mails' recommendations and search encouragement increase by around 1.5% the job finding rate of female job seekers (+0.26pp from a baseline of 17.43%). This seems to be primarily driven by an activation effect of our intervention that led to an increase in search effort. This additional effort appears to be concentrated on firms that are displayed on LBB's online platform — no matter whether or not these firms were specifically recommended to the job seeker in the e-mail they received. Nevertheless, we also document a targeting effect of our intervention: an increase in the likelihood that specific matches between pairs of job seekers and firms occur when we recommend such matches in our emails. This underlines the ability of the recommender system to redirect search effort, leaving room for a potentially beneficial reallocation of labor across labor markets. As a last step of the analysis, we therefore document effects on aggregate employment. We estimate that recommending job seekers to search toward nearby tighter occupations significantly reduces congestion frictions in slack markets from which search effort was displaced. On the flip side, this increases frictions in the “destination markets” of our recommendations. Yet the relative magnitude of these opposite effects suggest a net positive effect. Overall, this provides evidence, in a real set-up, that recommender systems can be used to reduce mismatch unemployment due to informational frictions.

This paper contributes to two main strands of literature. First, it fits into the growing literature on the labor market impacts of recommendation platforms. Labor economists started paying attention to the potential of the Internet as a match-making device in the early 2000s (Autor, 2001; Kuhn and Skuterud, 2004), with hope but little empirical evidence of its effect on job finding rates. A decade later, further research revived the interest for online job-ads platform with more encouraging observational evidence (Kuhn and Mansour, 2013; Kuhn, 2014). Yet a recent turning point of this literature has lied in the increased capacity to run online controlled experiments to robustly identify and estimate the causal effect of these online platforms on the matching process. Horton (2017) is among the first paper that documented such effects in this fashion, highlighting the potential of tailored online screening of applicants to increase the vacancy filling rate on the firm side of the market. Rather concurrently, Belot et al. (2018b) documented the potential of customized online advice to broaden the occupational scope of some job search scope in a small-scale lab experiment. Since then, further work has started to study the optimal design of labor market recommender systems (Alfonso Naya et al., 2021). However, to the best of our knowledge our work is the first to document the effect of one such algorithm *at scale*, in an experiment involving roughly a quarter of the entire french labor market.
Second, our paper builds on, and provides a well-suited application to, the literature on the design and the evaluation of policy interventions in the presence of interference. The concern that the overall effect of interventions in various domains (labor, health or education, for instance) may differ substantively from their partial equilibrium effect is not new. A recent literature uses innovative experimental or quasi-experimental designs to quantitatively assess the underlying crowding-out (or crowding-in) effects. Seminal papers include Miguel and Kremer (2004) and Crépon et al. (2013). These papers use randomized saturation designs where some local markets have a lower proportion of treated units than others. Though particularly compelling, this approach builds on noisy comparisons across a small number of local markets, and therefore suffers from limited statistical power. In our case, the direct effects of the recommendations are at best small, so that indirect effects are very unlikely to be statistically detectable from such comparisons. As an alternative, Hu et al. (2022) have recently forcefully advocated the use of variations in indirect exposure to treatments within local markets. They introduce the "average direct effect" (ADE) and the "average indirect effect" (AIE) and show how the sum of these two effects directly translates into policy relevant parameters. Our paper provides an illustration of the value of their approach.

The paper proceeds as follows. Section II sets up a basic model to illustrate the trade-off between congestion and occupational mobility costs, and to derive a simple sufficient statistic to assess whether recommendation are too far or too close. In Section III, we provide background information on LBB's job search platform. Section IV presents a workable solution to assign recommendations in an ex ante optimal way through emails advertising the platform. Section V presents the evaluation design and the data. Section VI provides the results on the private return to receiving the emails, and decomposes this impact into an activation and a targeting effect. Section VII analyzes whether our intervention generated social returns by reducing congestion frictions in slack markets, and reallocating labor to tight markets to help labor demand meet supply. Section VIII concludes.

II An illustrative model of optimal recommendations with interference effects

II.1 Identifying the direct and indirect effects of job search recommendations

Consider a local labor market with two homogeneous job seekers (indexed by $i \in \{1, 2\}$). They are looking for a job in the same occupation and the same commuting zone, or equivalently the same "local market." Two firms are willing to hire. The first firm, indexed by $j = 0$, looks for workers in the occupation of the job seekers: denoting by $d_{i,j}$ the "occupational distance" between firm j and the job seeker i, this implies $d_{i,0} = 0$ for both job seekers $i \in \{1, 2\}$. The second firm, indexed by $j = 1$, looks primarily for workers in a neighboring occupation, which we denote by $d_{i,1} = 1$ for $i \in \{1, 2\}$. Under the assumption that skills are not perfectly transferable from one occupation to the other, both job seekers are more likely to be hired when they apply to firm 0 in their own occupation. If both job seekers were to apply to the same firm, however, congestion or rationing effects may weigh negatively on each individual job seeker's labor market outcome. Indeed, when labor demand at each firm is not perfectly elastic, each job seeker probability of being hired in a given firm will depend on his own as well the other job seeker's application behavior. In practice these congestion effects might entice a social planner to divert some job seekers away from firm 0 and toward firm 1 in order to increase the aggregate job finding rate of the economy.

Consider a policy intervention that sends one recommendation to each job seeker. The recommendation can be either to apply to firm 0 or to firm 1. Let $R_i^j = 1$ denote the fact that we recommend firm j to job seeker i and $R_i^j = 0$ otherwise. Because each job seeker only receives one recommendation we know that:

$$R_i^0 + R_i^1 = 1$$

While this notation is very general and will be useful later on in order to accommodate settings with many job seekers and firms, for the purpose of the present simple example we will concentrate on the effect of a specific "treatment", namely directing job seekers away from firm 0 and toward firm 1 which is hiring in the neighboring occupation. To this end we define a more specific dummy variable W_i which will take the value 1 if job seeker i is directed toward firm 1 as opposed to firm 0:

$$W_i = R_i^1 = 1 - R_i^0$$

We assume that the two treatment variables W_1 and W_2 are independent and drawn from the same Bernoulli distribution with mean π.[2] In this setting the parameter π which stands for the probability to re-direct job seekers away from their origin occupation, governs the degree of job seekers reallocation across labor markets and would ideally need to be chosen optimally. To what extent should policy makers recommend that job seekers broaden their occupational search to neighboring markets? Assume that the objective function of the policy maker is the aggregate employment rate in this economy. As the two job seekers are homogeneous, the aggregate employment rate is equal to the employment probability of any of them, $\mathbb{E}(Y_i)$, where Y_i is the indicator variable equal to 1 if job seeker i is hired by one of the two firms. We assume that each job seeker only applies to one firm, so that he or she can only receive an offer from one of the two firms. Denoting Y_i^j the indicator variable equal to 1 if i is hired by h, one has

$$Y_i = Y_i^0 + Y_i^1.$$

Whether job seeker i is ultimately hired by firm j depends on three elements: (i) the occupational distance $d_{i,j}$ separating job seeker i's skills from firm j's requirements; (ii) conditional on $d_{i,j}$, on whether i applied to j; (iii) on whether the other job seeker $(-i)$ also applied to j. At this point let us make no explicit assumption on job seekers' application behavior, except that application decisions are taken independently. We assume that the application behavior of i toward j only depends on W_i while the application behavior of the other worker $-i$ only depends on W_{-i}. In general we can define potential outcome variables for each job seeker/firm pair (i, j) as:

$$Y_i^j(R_i^j, R_{-i}^j).$$

The fact that job seeker i's potential outcome at firm j is a also a function both of job seeker $-i$'s treatment outlines the fact that we do not in general expect SUTVA[3] to hold in this setting. Recalling that W_i stands for the fact of recommending firm 1 in the neighboring market as opposed to firm 0 in one's own market, potential outcomes can be re-written directly as functions of W_i and W_{-i} instead of the more general R_i^j. Under this convention worker i's potential outcomes write

$$Y_i^0(1 - W_i, 1 - W_{-i})$$

[2]This can be seen as from the researcher's perspective as a "Bernoulli trial" (with W_i being the treatment indicator), or as a "mixed strategy" from the policy maker's perspective. Of course, a corner solution may be optimal for the policy maker, with recommendation systematically made to firm 0 ($\pi = 0$) or to firm 1 ($\pi = 1$).

[3]"Stable Unit Treatment Value Assumption".

in firm 0 and

$$Y_i^1(W_i, W_{-i})$$

in firm 1, with $(W_i, W_{-i}) \in \{0;1\}^2$.

In this setting job seeker i's probability of being hired in firms 0 and 1 are functions of the degree of job seeker's reallocation π and of potential outcomes:

$$\mathbb{E}(Y_i^0) = (1-\pi)^2\mathbb{E}(Y_i^0(1,1)) + (1-\pi)\pi\mathbb{E}(Y_i^0(1,0)) + \pi(1-\pi)\mathbb{E}(Y_i^0(0,1)) + \pi^2\mathbb{E}(Y_i^0(0,0))$$

and

$$\mathbb{E}(Y_i^1) = \pi^2\mathbb{E}(Y_i^1(1,1)) + \pi(1-\pi)\mathbb{E}(Y_i^1(1,0)) + \pi(1-\pi)\mathbb{E}(Y_i^1(0,1)) + (1-\pi)^2\mathbb{E}(Y_i^1(0,0)).$$

Given that job seeker i's overall job finding rate is just the sum of Y_i^0 and Y_i^1, the effect of small change in π on job seeker is overall job finding rate can be expressed as a function of π and all eight potential outcomes as

$$\begin{aligned}\frac{\partial\mathbb{E}(Y_i)}{\partial\pi} = \frac{\partial\mathbb{E}(Y_i^0+Y_i^1)}{\partial\pi} \quad = \quad & -2(1-\pi)\mathbb{E}[Y_i^0(1,1)] + (1-2\pi)\mathbb{E}[Y_i^0(1,0)] \\ & +(1-2\pi)\mathbb{E}[Y_i^0(0,1)] + 2\pi\mathbb{E}[Y_i^0(0,0)] \\ & +2\pi\mathbb{E}[Y_i^1(1,1)] + (1-2\pi)\mathbb{E}[Y_i^1(1,0)] \\ & +(1-2\pi)\mathbb{E}[Y_i^1(0,1)] - 2(1-\pi)\mathbb{E}[Y_i^1(0,0)].\end{aligned} \tag{1}$$

Even though highly stylized, this model is rich enough to illustrate two important points. First, it shows that a policy maker can learn about the optimal π without necessarily testing alternative values of π across different local markets, as would be the case in a randomized saturation design. Instead, by picking a value of π (which can be chosen close to 0.5 in order to maximize statistical power, or close to priors on the optimal value π^*), the policy maker may estimate employment rates in firm j from a Bernoulli trial in which, due to random assignment, average potential outcomes are identified by

$$\mathbb{E}[Y_i^0(1-W_i, 1-W_{-i})] = \mathbb{E}[Y_i^0 \mid 1-W_i, 1-W_{-i}]$$

and

$$\mathbb{E}[Y_i^1(W_i, W_{-i})] = \mathbb{E}[Y_i^1 \mid W_i, W_{-i}].$$

With these potential outcomes in hand the social planner can compute the marginal effect on aggregate job finding of narrowing or widening job search and adjust π accordingly. The downside of this approach is of course that the policy maker only learns about the derivative of the objective function at the chosen value for π, $\partial\mathbb{E}(Y_i)/\partial\pi$, while a randomized saturation design varying π would identify $\mathbb{E}(Y_i \mid \pi)$ on a whole range of possible saturation levels (π).

Second, the expression in equation 1 is directly related to the sum of two average effects that Hu et al. (2022) call the average direct effect, τ_{ADE}, and the average indirect effect, τ_{AIE}. The average direct effect directly relates to what would be an average treatment effect in a design without interference: in our case the average effect of widening job seeker i's occupational search on job seeker i's own job finding rate. The average indirect effect on the contrary has no direct counterpart in a setting without interference. In presence of cross treatments interference, the average indirect effect is the average effect that widening any job seeker's occupational search has on the aggregate job finding rate of all other job seekers. In this setting the total effect of treatment on the average outcome is the sum of the direct and indirect effects. Recommending job seekers to concentrate their job search effort on neighboring occupations may have a direct negative effect on job finding because of skill loss, but an indirect average positive effect through decreased competition in the origin occupation, hereby increasing the aggregate job finding rate.

In our simple example with just two firms and job seekers, these two effect have simple expressions. Defining worker i's total potential outcome as a function of (W_i, W_{-i}):

$$Y_i(W_i, W_{-i}) = Y_i^0(1 - W_i, 1 - W_{-i}) + Y_i^1(W_i, W_{-i})$$

we can apply the definition in Hu et al. (2022) to express the average direct effect as:

$$\tau_{\text{ADE}} = \mathbb{E}[Y_i(W_i = 1, W_{-i}) - Y_i(W_i = 0, W_{-i})],$$

and the average indirect effect as:

$$\tau_{\text{AIE}} = \mathbb{E}[Y_i(W_i, W_{-i} = 1) - Y_i(W_i, W_{-i} = 0)].$$

Given that both W_i and W_{-i} follow independent Bernoulli laws of intensity π and that job seeker i's overall potential outcome Y_i is just the sum of Y_i^0 and Y_i^1, the average direct and indirect effect are given by:

$$\begin{aligned}\tau_{\text{ADE}} \quad = \quad & (1-\pi)\mathbb{E}[Y_i^0(1,1) - Y_i^0(0,1)] + \pi\mathbb{E}[Y_i^0(1,0) - Y_i^0(0,0)] \\ & + (1-\pi)\mathbb{E}[Y_i^1(0,0) - Y_i^1(1,0)] + \pi\mathbb{E}[Y_i^1(0,1) - Y_i^1(1,1)]\end{aligned} \tag{2}$$

and

$$\begin{aligned}\tau_{\text{AIE}} \quad = \quad & (1-\pi)\mathbb{E}[Y_i^0(1,1) - Y_i^0(1,0)] + \pi\mathbb{E}[Y_i^0(0,1) - Y_i^0(0,0)] \\ & +(1-\pi)\mathbb{E}[Y_i^1(0,0) - Y_i^1(0,1)] + \pi\mathbb{E}[Y_i^1(1,0) - Y_i^1(1,1)]\end{aligned} \tag{3}$$

Comparing equations 1, 2 and 3, one can check that

$$\frac{\partial \mathbb{E}(Y_i)}{\partial \pi} = \tau_{\text{ADE}} + \tau_{\text{AIE}}. \tag{4}$$

Equation 4 is a direct application of Theorem 1 in Hu et al. (2022). It states that the marginal impact of increasing the probability to recommend firm 1 at the expense of firm 0 is equal to the sum of an average direct effect (τ_{ADE}) and an average indirect effect (τ_{AIE}).

II.2 Congestion effects versus occupational distance

Keeping the exact same setting with two job seekers and two firms, a "model" of the labor market consists in a set of values for all potential outcomes. Closely mimicking the model actually used in our randomization process (see Section IV), let us assume that, conditional on receiving a recommendation, worker i applies with probability 1 at firm j whenever $d_{i,j} = 0$ and with probability $\rho < 1$ whenever $d_{i,j} = 1$. We assume that if not recommended to do so, job seekers do not apply to any firm. Once job seekers' applications have been sent to a particular firm they pass through the receiving firm's internal screening process. If a firm receives one application only, this unique application simply goes through to following steps of the hiring process. If a firm receives more than application, each application makes it through to later stages of the hiring process with probability $c \in [0.5; 1]$. The parameter c hence measures the degree of firm level congestion in the hiring process. If $c = 0.5$, only one application gets selected on average when two are received: there is full congestion. If $c = 1$, all applications are considered by the firm, there is no congestion. Once an application successfully passes through the screening step, firms decide to hire or reject the candidate based on his or her labor market skills. Mirroring job seekers' application decisions, we assume that firm j decides to hire interviewed candidate i with probability 1 if $d_{i,j} = 0$ and with probability $\mu < 1$ if $d_{i,j} = 1$.

Under these stylized assumptions the full set of potential outcomes can be described by:

$$
\begin{aligned}
&\mathbb{E}(Y_i^0(0,0)) = 0 \qquad && \mathbb{E}(Y_i^0(0,1)) = 0 \\
&\mathbb{E}(Y_i^0(1,0)) = 1 \qquad && \mathbb{E}(Y_i^0(1,1)) = c
\end{aligned}
$$

and

$$
\begin{aligned}
&\mathbb{E}(Y_i^1(0,0)) = 0 \qquad && \mathbb{E}(Y_i^1(0,1)) = 0 \\
&\mathbb{E}(Y_i^1(1,0)) = \rho\mu \qquad && \mathbb{E}(Y_i^1(1,1)) = \rho^2 \times c \times \mu + \rho(1-\rho)\mu \\
& && \qquad\qquad\quad = \rho\mu - (1-c)\rho^2\mu.
\end{aligned}
$$

In the absence of congestion effects (i.e. $c = 1$) the application behavior of other workers do not affect one's own outcome:

$$
\mathbb{E}(Y_i^0(1,0)) = \mathbb{E}(Y_i^0(1,1)) = 1
$$

$$
\mathbb{E}(Y_i^1(1,0)) = \mathbb{E}(Y_i^1(1,1)) = \rho\mu.
$$

Moreover, the effective congestion effect defined as the percentage fall in hiring probabilities when one more worker gets recommended to the same firm decreases in absolute value from $c - 1 < 0$ at $d_{i,j} = 0$ to $\rho(c-1)$ at $d_{i,j} = 1$. The decline of congestion effects with occupational distance arises because less and less recommendations transform into actual applications once $d_{i,j} > 0$.[4]

[4] We define the effective congestion effect at firm j as:

$$
\frac{\mathbb{E}(Y_i^j(1,1)) - \mathbb{E}(Y_i^1(1,0))}{\mathbb{E}(Y_i^1(1,0))}.
$$

Substituting for potential outcomes in the marginal effect of π defined above we get:

$$\frac{\partial \mathbb{E}(Y_i)}{\partial \pi} = -2(1-\pi)c + (1-2\pi) + 2\pi[\rho\mu - (1-c)\rho^2\mu] + (1-2\pi)\rho\mu$$

Given this expression and assuming that $E(Y_i)$ is a concave function of π we can solve for $\pi^\star$ the optimal degree of redirection of workers away from their origin occupation — $\pi^\star = 0$ corresponding to no redirection at all while $\pi^\star > 0$ entails that some workers are recommended to firms hiring outside of their origin occupation.[5]

A solution to this problem displaying a positive amount of worker reallocation across labor markets exists if and only if:

$$1 + \rho\mu > 2c.$$

As a consequence job seekers' reallocation across labor markets will never be optimal when the cost of occupational distance is high (i.e. if μ and/or ρ are sufficiently close to zero) and/or when congestion effects are low (i.e. when c is close to 1). Notice that if there are no costs to occupational switching ($\rho = \mu = 1$) then a central planner would be indifferent between the two available job search strategies $\pi^\star = 1/2$, regardless of the degree of congestion effects c.

Overall, the fact that the optimal policy depends on mobility costs as well as on the strength of congestion effects suggests that it is likely to vary across local labor markets defined by occupations and geographical location. The goal of this study is to explore empirically optimal reallocation policies in a real setting with thousands of firms and job seekers interacting in connected labor markets.

III Context: "La Bonne Boîte," an online job search platform

This study builds upon a pre-existing platform, "La Bonne Boîte" (LBB). This platform has been operated by the French Public Employment Service (PES) since 2015, that is for five years before the experiment presented in this paper. In this section, we briefly review the main pre-existing features of the platform.

LBB is an online job search platform that aims to help them in their search by encouraging them to make unsolicited (spontaneous) applications. It can be accessed by any job seeker without registration, and works as a search engine: job seekers indicate a geographical area and an occupation of search (see Figure A1) and LBB proposes a list of firms kely to hire them (see Figure A2). Once they click on a firm of interest an email address and/or phone contact the firm directly is given (see Figure A3).

[5] If an interior solution exists it is given by:

$$\pi^\star = \frac{1 + \rho\mu - 2c}{2(1-c)(1+\rho^2\mu)}.$$

The distinguishing feature of LBB is to recommend firms deemed likely to hire, whether they have posted a job advertisement or not. The rationale is to reduce informational frictions by allowing job seekers to apply to the "hidden job market" of firms that have potential vacancies that they fill without posting jobs (through internal referrals, for instance). To do so, LBB uses administrative data covering the universe of French firms to derive hiring predictions at the establishment $\times$ occupation hiring predictions.[6] LBB then defines for each occupation a specific predicted hiring threshold above which an establishment is deemed a "hiring firm" (sometimes denoted by BB for "Bonne Boîte" in french) for this specific occupation.[7] If there is no such establishment, LBB's search engine suggests to extend the search to a wider geographical area.

We do not have a leeway on the algorithm used to predict hiring, and take it as given. However, we are sufficiently confident in the quality of LBB's prediction for our purpose: their prediction does explain realized hirings. Figure A6 plots the relationship between the log of firms' average predicted hiring, within twenty equal-size groups, and the log of realized average hiring in each of those groups of firms. The figure also plots the linear correlation between the logs of predicted hiring and realized hiring, estimated on the individual data. The correlation coefficient is 0.89, with an R-squared of 0.37, and significant at the 1% level.

In its business-as-usual mode, LBB only recommends firms likely to offer jobs in the occupation the job seeker entered in the search engine. In the next section, we present the additional algorithm that we develop to generate recommendations to broaden the occupational search. Then, in Section V, we present the evaluation design to assess the impact of this experimental development.

IV A workable optimal recommendation system

IV.1 Structure of the intervention and expected number of matches

While the simple model of section II underscores the fact that optimal recommendations tightly depend on the occupational structure of the labor market as well as the strength of potential congestion effects, the model is not general enough to generate actual labor market recommendations. To that end we extend the model of section II to a setting involving many workers and firms with occupational distances strictly greater than 1 while allowing for congestion effects to depend continuously on the number of applications received by each firm. Our experimen-

[6]These predictions are derived from establishment level predictions which are then mapped into establishment $\times$ occupation hiring prediction using a sector-occupation crosswalk. This crosswalk is based on the share of each occupation hirings within each sector. This share was computed for registered unemployed exiting unemployment between the 02.03.2016 and 31.03.2017 (https://www.data.gouv.fr/fr/datasets/nombre-dembauches-par-code-ape-et-code-rome/).

[7]As a consequence, a given establishment can be considered as a "hiring firm" for one occupation but not for another.

tal design will heavily rely on this more general model to generate recommendations that are not purely arbitrary, while introducing controlled sources of variation (see details in Section V below).

Workers and firms Because our experiment will only involve within commuting zones recommendations we focus on a spatially homogeneous labor market and deliberately ignore the potential role played by geographical frictions in determining labor market outcomes. A labor market is populated by I workers and h firms. On the worker side we use an exhaustive list of registered job seekers actively looking for a job within each commuting zone. Beside important demographic characteristics (gender, age, experience, diploma, nationality, etc), we also know in which specific occupation each job seekers is currently searching. This occupation may or may not be identical to the occupation in which a job seekers was previously working. On the firm side we directly recover the set of firm level predicted hirings from LBB's platform. Following LBB's prediction algorithm we assume that each firm can hire workers in one of H different occupations. We denote firm j's predicted hirings or "vacancies" in occupation h as $V^{j,h}$.

Occupational distance The notion skill or occupational distance is central to our recommendation algorithm. We measure skill distance between any two occupations as the shortest path in the occupational graph defined by public employment services' set of "close" occupations. "Close" occupations are occupations between which job seekers are able to transition without any form retraining. Linking close occupations together we construct the network of occupations implied by skill proximity in the french ROME classification (532 occupations). Occupational distance $d_{h,h'}$ between any two occupations h and h' is defined as the shortest path linking these occupation in the occupational network. What's more, denoting $h(i)$ job seeker i's search occupation, we abuse notations and define the occupational distance $d_{i,j}$ between job seeker i and firm j as the minimum distance between job seeker i's search occupation $h(i)$ and the set of occupation for which firm j has positive predicted hirings V^j :

$$d_{i,j} = \min_{h|V^{j,h}>0} d_{h(i),h}$$

With this definition of worker/firm occupational distance in hand, we now turn to the exposition of our recommendation algorithm.

Targeted recommendations Given the observed joint distribution of job seekers and firms in a given commuting zone, we will use our statistical model generate a set of targeted job search recommendations so as to maximize the expected number of worker/firm matches. As a consequence, the central object of our experiment is the distribution joint distribution of worker/firm recommendations. At the outset of the experiment we start by fixing the total number of tailored recommendations which will be received by each job seeker. Denoting this number by N_i for job seeker i, the total number of recommendations we want to generate is given by:

$$N = \sum_{i \leq I} N_i$$

In practice we repeatedly draw these N_i recommendations from a worker specific generalized Bernoulli distribution over all possible firms with positive predicted hirings. Our statistical model of worker/firm matches should be rich enough to solve for the set of optimal generalized Bernoulli non-negative probability weights

$$0 \leq \alpha_i^j \leq 1$$

verifying

$$\sum_{j \leq J} \alpha_i^j = 1$$

where α_i^j is the probability to recommend firm j to worker i in each single draw of the generalized Bernoulli distribution. Taking as given N_i the number of tailored recommendations which will make to job seeker i, the probability to recommend firm j to job seeker i at least once is given by:

$$P(R_i^j = 1) = 1 - (1 - \alpha_i^j)^{N_i}$$

where the random variable R_i^j takes the value 1 if we recommend firm j at least once and 0 otherwise.

Expected number of matches Letting Y_i^j denote the random variable which takes the value 1 if job seeker i is eventually hired by firm j, our objective is to select the distribution of worker specific recommendations so as to maximize the expected number of matches in the economy :

$$Y = \mathbb{E}[\sum_{i,j} Y_i^j]$$

which can be rewritten as:

$$Y = \sum_{i,j} \mathbb{E}[Y_i^j | R_i^j = 1] \times [1 - (1 - \alpha_i^j)^{N_i}] + \mathbb{E}[Y_i^j | R_i^j = 0] \times [1 - \alpha_i^j]^{N_i}$$

When the number of available occupations and firms is large enough so that each α_i^j is relatively small this expected number of hirings can be approximated as:

$$H \sim \sum_{i,j} (\mathbb{E}[Y_i^j | R_i^j = 1] - \mathbb{E}[Y_i^j | R_i^j = 0]) \times N_i \times \alpha_i^j$$

up to a constant, where the first term is a measure of the aggregate effect of our intervention and highlights the fact that a greater weight α_i^j should be placed on worker/firm pairs with a high expected gain from recommendation $\mathbb{E}[Y_i^j|R_i^j = 1] - \mathbb{E}[Y_i^j|R_i^j = 0]$. In order to concentrate on the effect of targeted recommendations we will from now on normalize all default outcomes $\mathbb{E}[Y_i^j|R_i^j = 0]$ to zero. Under this normalization our main object of interest is worker i's probability of being hired in firm j conditional on being recommended to apply to this position. In the rest of this section we put more structure on workers' conditional hiring probabilities closely following the intuition outlined in section II.

IV.2 A flexible model of worker/firm matches

In this subsection we outline a simple model of workers' application strategies and firms' hiring decisions which generalizes section II's model to occupational distances strictly greater than 1 while allowing firm level congestion effects to depend continuously on the number of applicants.

Modeling job seeker's application strategies On the worker side, we assume that each job seeker i may look for a job in his origin occupation as well as neighboring occupations. Very much like in the stylized model of section II each worker is characterized by an idiosyncratic distaste for occupational distance $\rho_i \in (0, 1)$. Conditional on receiving a recommendation to apply to firm j, we assume that worker i applies to firm j with probability

$$P(A_i^j = 1) = \rho_i^{d_{i,j}}$$

where the random variable A_i^j takes the value 1 if worker i applies to firm j and 0 otherwise. This simple parametric assumption generalizes section II's setting to occupational distances greater than one.

Firm's hiring strategies To simplify our statistical model of worker/firm matches we assume that hiring decisions are taken at the firm level and are not correlated within firm across different occupations. In other words, we consider each firm pair as an independent hiring unit. Given workers' application behavior firm j will on average receive

$$A^j = \sum_i \rho_i^{d_{i,j}} R_i^j$$

applications.[8] Upon receiving these occupation specific applications, firm j randomly selects a proportion $q^j \in (0, 1)$ of them. We assume that this proportion of successful application continuously depends on the ratio of received application A^j to predicted hirings V^j. Let $\theta^j = A^j/V^j$ denote this measure of firm level slackness, we set the screening rate q^j to:

$$q^j = q_j(\theta^j)$$

[8]Where we implicitly assume that workers' probability to apply in an un-recommended firm is 0.

where q_j is a firm specific screening function verifying $q_j \in (0,1)$, $q_j' \leq 0$, $q_j(0) = 1$, and $q_j(+\infty) = 0$.[9] This firm specific screening function plays the role of the c parameters of section II and models firm level congestion costs. Notice that while we allow the screening function to vary across firms (so as to model different levels of firms' screening efficiency), we restrict screening efficiency to be constant within firms and across occupations. Conditional on applying to j a worker can expect to be interviewed with probability:

$$\tilde{q}^j = \mathbb{E}[q^j] = \mathbb{E}[q_j(\theta^j)]$$

Because in general q_j is non linear we approximate this expectation through a second order Taylor expansion:

$$\tilde{q}^j \sim q_j(\mathbb{E}[\theta^j]) + \frac{\mathbb{V}[\theta^j]}{2}\frac{\partial^2 q_j}{\partial \theta^2}(\mathbb{E}[\theta^j])$$

where $\mathbb{E}[\theta^j]$ and $\mathbb{V}[\theta^j]$ can be computed explicitly.[10] Finally, screened applicants go through a final step in which the firm decides to hire or reject each applicant based on occupational distance. We denote each firm's distaste for occupational distance μ_j and, as in the worker case, assume that each screened applicant probability of success is given by $\mu_j^{d_{i,j}}$.

Summing up the hiring process and hiring probabilities Summing up the hiring process we have just described we can break down our statistical model of worker/firm matches into the following steps:

1. We recommend firm j to worker i.

2. Worker i who is more or less averse to occupational distance $d_{i,j}$ applies to firm j with probability $\rho_i^{d_{i,j}}$.

3. Firm j skims through the applications it receives and randomly decides to look more deeply into q^j of them.

4. Firms are more or less efficient at screening applications. More efficient firms will be able to review a greater number of applications.

5. Firms, which are more or less averse to occupational switching, review selected applications and decide whether or not to hire each reviewed applicant according to occupational distance. Each screened applicant is hired with probability $\mu_j^{d_{i,j}}$.

[9] See appendix A.7 for further details.

[10] Under the assumption we made on workers' application process we know that

$$\mathbb{E}[\theta^j] = \frac{\mathbb{E}[A^j]}{V^j} = \frac{\sum_i \rho_i^{d_{i,j}}(1-(1-\alpha_i^j)^{N_i})}{V^j}$$

and

$$\mathbb{V}[\theta^j] = \frac{\mathbb{V}[A^j]}{(V^j)^2} = \frac{\sum_i \rho_i^{d_{i,j}}[1-(1-\alpha_i^j)^{N_i}][1-\rho_i^{d_{i,j}}[1-(1-\alpha_i^j)^{N_i}]]}{(V^j)^2}$$

Combining all these steps allows to pin down the unconditional probability that worker i is hired by firm j in our experimental setting as:

$$\mathbb{E}[H_i^j|R_i^j = 1] \sim \mu_j^{d_{i,j}} \times \tilde{q}^j \times \rho_i^{d_{i,j}}$$

Substituting for $\mathbb{E}[H_i^j|R_i^j = 1]$ in the expression for H the expected total number of matches created by our intervention gives:

$$H \sim \sum_{i,j} \mu_j^{d_{i,j}} \times \tilde{q}^j \times \rho_i^{d_{i,j}} \times [1 - (1 - \alpha_i^j)^{N_i}]$$

which is a non linear function of the Bernoulli weights central to our experimental design.

Finding the optimal recommendation weights in practice The problem of the central planner is to maximize H over the space of possible worker specific distribution of recommendations. This problem has dimensionality #(Workers) $\times$ #(Firms) $\times$ #(Occupations), which is of course too large to solve through brute force. To reduce the dimensionality of the problem we parameterize α_i^j using available information on workers and firms. Denote X_i^j the vector of worker/firm characteristics that will be used to predict α_i^j. We assume that:

$$\alpha_i^j = \frac{\exp(\beta X_i^j)}{\sum_j \exp(\beta X_i^j)}$$

Hence the dimensionality of the problem is reduced to #(worker/firm characteristics) so that, in the end, the maximization problem reduces to:

$$\max_{\beta} \sum_{i,j} \mu_j^{d_{i,j}} \times q^j \times \rho_i^{d_{i,j}} \times [1 - (1 - \frac{\exp(\beta X_i^j)}{\sum_j \exp(\beta X_i^j)})^{N_i}].$$

In practice the vector X may includes observable market level, worker level and firm level characteristics, taken both from observed data (firm level predicted hirings, worker/firm occupational distance) and structural parameters of the model (μ_j, ρ_i, the shape parameters of the screening function q_j.) The weight given by the optimal parameter β to these different components will depend on the occupational distribution of job seekers and firms within each geographically defined labor market. In a case where job seekers and firms would operate in very different occupations, large aggregate gains should be expected from reallocating workers across occupations so that the optimal β would but little negative weight on occupational distance in forming pairwise worker/firm recommendations. The exact opposite would occur if worker and firm were to be evenly distributed across the occupational space.

V Experimental design

This study builds upon a two-sided randomization that creates random exposure to recommendations by LBB on the firms' and job seekers' sides. In this section we first describe how we selected treated firms and job seekers who were included in the experiment and then turn to the drawing of pairwise recommendations linking the two sides of the markets.[11]

V.1 Drawing treated job seekers and treated firms

All experimental treatments are assigned within commuting zones.[12] Our experimental sample covers 94 out the of the 404 French commuting zones,[13] representing a pool of $1,209,859$ job seekers and $98,366$ hiring establishments.

The basic experimental treatment consists in increasing treated firms' and treated job seekers' exposure to LBB's job search services. First, we randomly select a subset of firms among those short-listed by LBB's algorithm. We stratify the random selection of treated firms within 5-digits sectors and above median/below median predicted hiring bins. During four weeks, selected "treated" firms are displayed in priority in response to job seekers' requests on the website, while the remaining "control" firms are not displayed (or displayed at the bottom of the list if there are too few treated firms satisfying the search criteria). Second, we randomly draw two thirds of the 1.2 million job seekers to receive two or four emails pushing the LBB service, with specific recommendations toward up to eight of the treated firms. We stratify the random selection of treated job seekers within desired occupations and above median/below median bins of a linearly predicted exit rate out of unemployment.

We randomly draw $806,437$ treated job seekers and $38,810$ treated establishments. Because a large share of job seekers exited the unemployment pool in the short period separating randomization from the actual start of our experiment, we will ex-post restrict our analysis to the $533,557$ treated and $266,740$ control job seekers who were still registered with PES and had not found a job as of 19th november 2019.[14]

The balance of job seekers' observable variables across treatment and control groups is presented in Table 1, keeping only job seekers still unemployed at the beginning of the experiment. Furthermore this table presents the p-values associated to an F-Test of the regressions of each observable on four indicator variables corresponding to the four job seekers' treatment arms.

[11]We do not insist on the firm-level randomization, whose analysis is the focus of a companion paper.

[12]When assigning treatment within a commuting zone, we do not distinguish across job seeker and establishment pairs by their geographical distance. Indeed, the existing evidence suggests that spatial mismatch is second order compared to occupational mismatch (Marinescu and Rathelot, 2018). The role of geographical distance can however be analyzed ex post based on remaining non-experimental variation; this is kept for further analysis.

[13]We randomly selected these 94 Commuting Zones out of all the 404 possible commuting zones. We stratified this random selection of treated commuting zones within tightness and size quintiles. For more details on Commuting Zones and local labor markets see Appendix Section A.3.

[14]This pre-treatment attrition rate is be well balanced across treatment and control groups.

Table 1: Balance table for job seekers in treated CZ.

	(1) Control		(2) Treated		(3) Treated-Control	
Gender	0.450	(0.498)	0.451	(0.498)	0.001	(0.001)
Age	38.944	(12.052)	38.975	(12.043)	0.030	(0.029)
Diploma	0.608	(0.488)	0.608	(0.488)	-0.000	(0.001)
Experience (y)	6.917	(8.198)	6.920	(8.202)	0.003	(0.019)
Unemployment spell (m)	21.258	(24.724)	21.313	(24.807)	0.055	(0.059)
Predicted exit rate	0.207	(0.072)	0.207	(0.072)	0.000	(0.000)
Predicted tightness	0.392	(0.660)	0.391	(0.666)	-0.000	(0.002)
Observations	266,740		533,557		800,297	

Note: Standard errors are displayed in parentheses. Column (1) presents

V.2 Drawing pairwise recommendations

V.2.1 Additional treatment arms

Even though the random selection of a pool of treated job seekers and a pool of treated establishments tells us which job seekers and which establishments will enter our pairwise recommendations, it does not tell us which specific pairwise recommendations will be formed. In particular, should a given job seeker receive recommendations only toward firm likely to hire in their local labor market, or should recommendations be broadened toward firms likely to hire in neighboring occupations? As illustrated in Section II and further detailed in Section IV, the optimal solution depends on the position of the job seeker in the occupational space, and on the relative tightness in the occupations that surround him. Importantly, the specific solution depends on unknown parameters on mobility cost and congestion effects. The goal of our experiment is precisely to learn about the optimal solution. This requires to introduce random variation in the recommendations made. We do so by hypothesizing several plausible parameter values related congestion and mobility costs, and randomly assigning those values across firms and workers, thus defining additional treatment arms among treated job seekers and treated firms.

Specifically, we do not a priori known (a) *how many* recommendations job seekers and establishments should receive for these recommendations to have an effect. Secondly, we do not a priori know (b) *how far* in the occupational space we should advise job seekers and establishments to look for jobs and employees. In order to get a sense for (a) and (b) we build into our experimental design a further level of randomness by distributing 4 possible treatment status among treated job seekers and establishments, using a factorial design. Hence while among treated job seekers some will receive **many** recommendations, others will only receive a **few**. At the same time some treated job seekers will be recommended to establishments hiring **far away** in the occupational space while others will be recommended to establishments hiring **close to** their own occupation. Similarly, while some establishments will be recommended to large pool of job seekers *conditional* on their level of predicted hiring some other establishments will only be recommended to few job seekers. And while some establishments will be recommended to occupationally close-by job seekers, others will be recommended to job seekers far away in the occupational space. We sum up the structure of our experimental design and the distribution of the different treatment status for job seekers and establishments in Table 2.

Table 2: Treatment arms and recommendations types

	Job-seekers				**Establishments**		
	Treated		Control		Treated		Control
	Few	*Many*			*Few*	*Many*	
Close	133,558	133,619	266,740	*Close*	9,716	9,614	59,556
Far	133,169	133,411		*Far*	9,792	9,688	

V.2.2 Applying the optimal recommendation algorithm

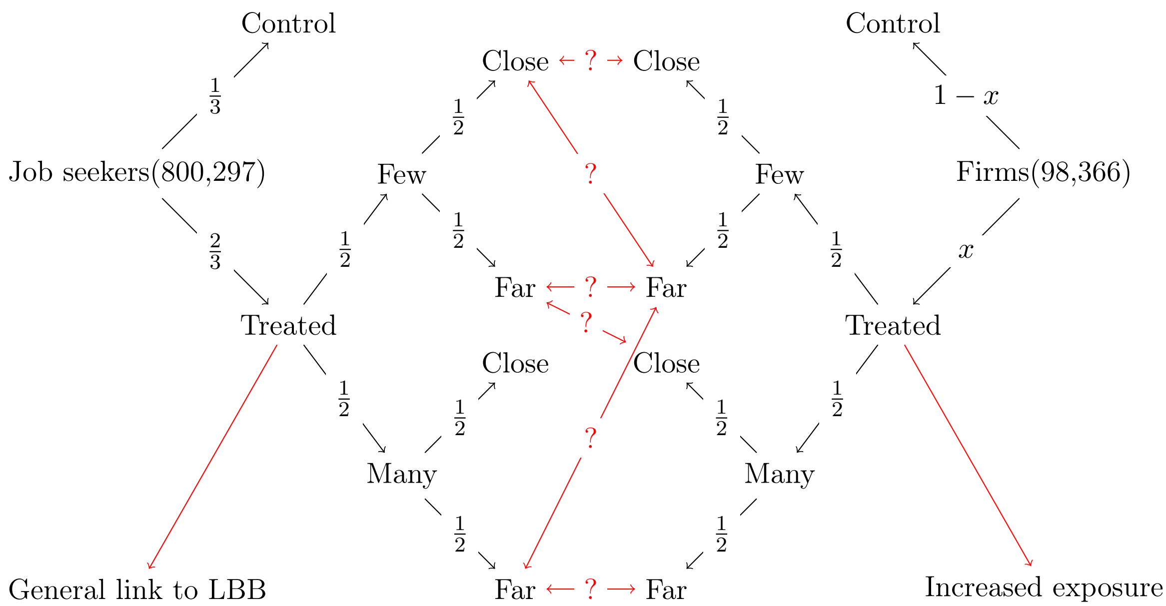
Based on their treatment arm, we assign job seekers and firms with specific values of the key parameters of the model of Section IV. The first one is N_i the number of recommendations received by job seeker i, which we take to be four in the "few" treatment arm and eight in the "many" treatment arm.[15] The other parameters are ρ_i and μ_j, the occupational distaste parameters on the worker's and firm side respectively. According to each agent's "far" or "close" treatment arm we select either a high value of these count factor, corresponding to a low distaste for occupational distance in the "far" group, or a low value corresponding to a strong distaste for occupational distance in the "close" group. Finally we model the strength of firm level congestion effects through a firm specific shift term m_j entering the screening function q. Firms in the "many" treatment arm are characterize by a high value of the screening efficiency m_j while firms in the "few" treatment arm are attributed a low value of m_j. As a consequence our recommendation algorithm should attribute relatively more recommendations to the "many"-type firms than to the "few"-type ones.[16]

With these random structural parameters in hand we turn to the recommendation model described in Section IV. We take firm level predicted hirings as our empirical counterpart of opened vacancies and solve for the optimal weights β in each of the 94 commuting zone. As could be

[15] In practice, a job seeker assigned to the **many** treatment may not receive eight distinct recommendations, if the same firm pair is drawn more than once.

[16] In practice we select $N_i \in \{4, 8\}$, $\rho_i \in \{0.82, 0.94\}$, $\mu_j \in \{0.82, 0.94\}$ and $m_j \in \{0.5, 1.5\}$. The curvature of the screening function is set to 3, see appendix A.7 for further details.

Figure 1: Treatment arms for job seekers and firms



expected, occupation distance as well agents' distaste of it affect the probability of a far away recommendation negatively. The firm level screening efficiency parameter attributed in the "few"/"many" treatment arms increases the expected number of recommended job seekers. Finally, everything else equal, large firms are also more likely to receive many recommendations. Once the optimal weights β are numerically solved for in each commuting zone we proceed to draw as many job seeker/firm recommendations as needed following the generalized Bernoulli distribution described in section IV.

For instance, for a job seeker i assigned to the "many" and "far away" treatment arms, we draw eight times from the pool of available firms with a probability α_i^j where α_i^j is the optimal solution for a job seeker in this particular local market who was attributed a low mobility cost (large ρ), given the mobility costs, screening efficiencies and predicted hirings of all job seekers and firms who surround him or her.

In the end, on both sides of the market, each agent's treatment status determines how many recommendations he will receive and how far these recommendations will be in the occupational space. Hence, while our pairwise recommendations partly reflect the non-random empirical distribution of job seekers and predicted vacancies across the occupational space, they also incorporate a random component linked to each agent's specific treatment status which will allow us to identify the effect of the number of recommendations and their occupational distance.

As can be seen in Table 3, on average job seekers belonging to the "Few" treatment arm received recommendations to 3.19 distinct establishments while job seekers belonging to the "Many" treatment arm, received recommendations to 5.62 distinct establishments. In both the "Few" and "Many" treatment arms, the relative occupational distance of these recommendations varied according to each job seeker's "Close" or "Far" treatment status. Whereas job seekers bound to receive "Close" recommendations were kept at a 0.55 average distance, job seekers in the "Far" treatment arm were set recommendations on average 1.28 occupations away from their original search occupation.

Table 3: JOB SEEKERS' REALIZED TREATMENT

		Mean	Sd	Min	Max	Obs
Distinct rec.	Few	3.19	1.07	1	4	399821
	Many	5.62	2.34	1	8	399938
Occupational dist.	Close	0.55	1.19	0	15	400504
	Far	1.28	1.56	0	15	399705

Note: This table gives descriptive statistics for the number of distinct recommended firms in the "Few" versus "Many" job seekers' treatment arms as well as the average occupational distance of job seekers' recommended establishments in the the "Close" versus "Far" treatment arms.

V.3 Emailing job seekers with tailored recommendations

In practice, our experiment consists in emailing treated job seekers with links to LBB's contact information of specific firms. Job seekers interested recommended firms may contact them to make an unsolicited application. Importantly the contact information usually consists of a location, an email or a telephone number. When no contact information is available for a given establishment, LBB allows its user to directly search for this information on Google. Moreover, in some cases LBB allows job seekers visiting its pages to directly send an application through public employment services' online application tool. When this tool is available, and as can be seen in Figure A3 in appendix, job seekers just need to click on a "Send an application" (in French "Postuler") icon which appears on the right hand side of the contact information page.

As can be seen in Table 4 below or Figure A4 in appendix, the emails we used to direct job seekers to specific establishments contained the following information: the job seeker's name, general information on the hiring behavior of firms - and in particular on the fact that a considerable share of hirings stem from unsollicited applications -, general information on LBB, each job seekers desired occupation, at most two links to the LBB page of recommended establishments and, finally, a general purpose link directing toward LBB's search engine. Apart from the job seeker's name and search occupation the only specifically individual content of these emails were the links to the contact information of recommended firms. Importantly these links were job seeker/establishment specific so that by tracking job seekers' clicks we could record their interest in some specific establishment. How were this links formed and dispatched into different emails? As previously explained we drew within the pool of nearby treated establishments as many establishments, i.e. either 4 or 8, as each job seeker's treatment status required. Once these 4 or 8 recommendations had been drawn for each job seeker we distributed them respectively into either 2 or 4 different emails. Each email thus contained at most two links directing to the contact information of at most two distinct establishments. When a single establishment ended up appearing twice in a single email we collapsed the two links into one single link. Finally we distinguished between establishments hiring in a job seeker's own occupation and establishments hiring in another occupation by explicitly acknowledging one of the two cases when introducing each link. Establishments hiring in one's own occupation were introduced as such while establishments hiring in a neighboring occupation were framed as "hiring in an occupation not far from yours". After the specific links to recommended establishments' contact information, the email concluded with a general purpose link directing to LBB's search engine. The content of our emails is summed up in Table 4 below.

Table 4: An email's schematic content

Dear Mr./Mrs. [X], You are currently registered with the public employment services and are looking for a job as a [X's occupation]. Did you know that 7 out of 10 firms take into consideration unsolicited applications before actually posting a job-offer? "La Bonne Boîte", an online platform linked to public employment services, has selected for you a few firms which might be interested in your profile. Here is one that is likely to be interested in [your profile/a profile close to yours]: - [Link to recommended establishment 1] And another one that is likely to be interested in [your profile/a profile close to yours]: - [Link to recommended establishment 2, if any] You can send them your application. By clicking on [this link/these links] you will be able to contact [this firm/these firms] thanks to the coordinates that will appear or by using PES' online application tool if it is available. You may also search for other firms on LBB's website [general purpose link] Yours sincerely,

V.4 Reallocating labor across tight and slack markets

As we already made it clear in previous sections, our experiment aims at uncovering the potential of recommender systems to reduce mismatch unemployment. Indeed, this appears to be the main channel through which such devices could generate social returns.

A necessary condition for such recommender system to reduce mismatch unemployment is that it generates recommendations from slack labor markets (where labor is too abundant compared to the amount of posted vacancies) to tight markets. In that way, one can hope that the system reduces congestion frictions in slack markets while helping labor demand to meet supply in tight ones. Table 5 checks that it is the case of our recommendation algorithm in practice.

The average market in our experiment has around 23 job seekers for 10 hiring firms (BB). Its tightness, defined as the number of predicted hiring in hiring firms over the number of job seekers, is at 0.37. The median number of neighboring markets that are directly connected to any given market m in the occupational graph we use is 2. However, this hides a lot of heterogeneity across markets. This is why we distinguish in panels B and C of Table 5 two kinds of markets — the so-called "source" and "destination" markets. Source markets are those for which our algorithm generated an above median probability to make recommendations to neighboring occupations. In other words, these are the markets from which we re-oriented job seekers the most. These markets differ from the average market in key dimensions. They are smaller on average, with around 10 job seekers for 3 hiring firms. More importantly, their tightness measure is below the average over all markets, at 0.17. As mentioned above, this is a key property to be fulfilled for our algorithm to generate social gains: it should reallocate labor from slack to tight markets. Reassuringly, our algorithm appears to satisfy this condition, as our source markets seem to be slack markets. On the contrary, the destination markets — defined as those for which our algorithm generated an above median probability to make recommendations to neighboring occupations — appear to be bigger and tighter markets. The average number of job seekers in those markets is around 35, for 16 hiring firms. And their average tightness is at 0.56 (compared to 0.17 in source markets), suggesting that our redirection intervention towards such markets could contribute at reducing some existing mismatch unemployment.

Table 5: Tight and slack labor markets descriptive statistics

Nb. markets	Nb. job seekers	Nb. hiring firms (BB)	Tightness	Median nb. of neighboring markets (d=1)
A. All markets				
35187	22.74	9.53	0.37	2.01
	(72.82)	(37.05)	(1.01)	(1.66)
B. "Source" markets (above median prob. to recommend to neighboring occ.)				
17593	10.32	2.69	0.17	1.90
	(45.16)	(18.66)	(0.61)	(1.69)
C. "Destination" markets (below median prob. to recommend to neighboring occ.)				
17594	35.17	16.37	0.56	2.13
	(89.86)	(47.99)	(1.26)	(1.62)

Notes: Columns 2, 3 and 4 of this table report the average number of job seekers and hiring firms (BB) and the average tightness (as measured by the number of predicted hirings over the number of job seekers) for all or different categories of markets — with standard deviations reported in parenthesis. The last column reports the average number of directly neighboring markets — i.e., markets at distance 1 in the occupational graph we use. "Source markets" are defined as those within which job seekers faced a below median average probability to get recommendations outside of their market — the median probability being at 0.97. "Destination markets" are defined as those within which job seekers faced an above median average probability to get recommendations outside of their market.

VI Private returns to the encouragement: Activation and targeting effects

In this section, we start by providing reduced-form evidence that receiving the email increased job finding rates especially among female treated job seekers. We further decompose the reduced-form effects into a targeting and an activation effect, showing that the increased job finding rates occur through hirings both in recommended and in non-recommended firms. In a second step, we focus the analysis on pairs (dyads) consisting of a job seeker and a firm. We show that our design allows us to quantify the relative magnitude of the activation and the targeting effects, and confirm the existence of a stronger activation effect among female job seekers.

VI.1 Impact on job finding rates

We observe access to employment as registered by PES, over a period of four months since treatment. More specifically we know each job seeker's return to employment status, type of contract, the date at which this contract is set to start and, for definite duration contracts, the date at which this contract will be terminated. The main equation we estimate by OLS is the following:

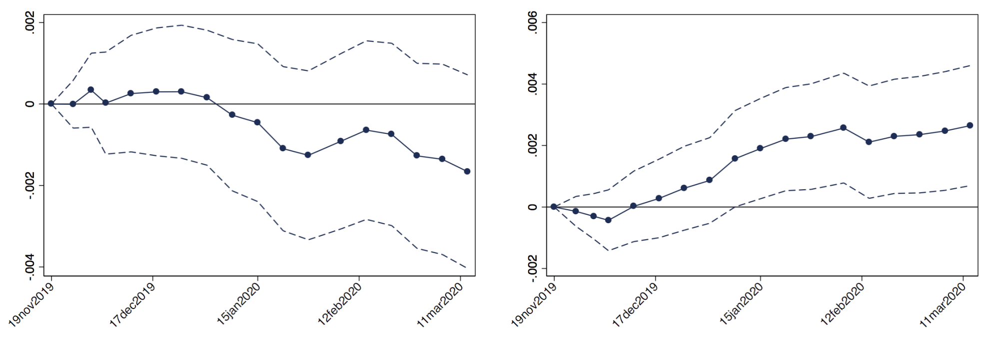
$$y_i = \alpha + \beta Z_i + \epsilon_i.$$

The dependent variable of interest y_i corresponds to the job finding status of job seeker i at a given point in time, possibly conditioning on the type of contract found (finite or indefinite duration). Z_i is a dummy equal to 1 if job seeker i received an email. This model is estimated in the sample of treated and control individuals from treated commuting zones, and $\hat{\beta}$ is therefore an estimator of our "intention to treat" (ITT) parameter on the job seeker's side.[17]
Figure 2 presents the estimates of this ITT parameter at different time horizons pooling together all types of contract, for the subsample of male (panel a) or female (panel b) job seekers.[18] Each point depicts the result of a separate regression of access to employment before some date on the treatment status Z_i for the set of job seekers who were still unemployed when our intervention began. Going from left to right, the time horizon widens so that the overall graph depicts the cumulative effect of our treatment on job finding.

[17] We describe β as an ITT parameter as a large share of "treated" job seekers ($Z_i = 1$) did not even open the e-mail we sent them in the first place. Therefore, we see our e-mail as an encouragement rather than a proper treatment in itself.

[18] Figure A8 in appendix reports the point estimates for the full sample, pooling male and female job seekers together.

Figure 2: Job-finding rate ITT estimates by gender



(a) Males (b) Females

Note: ITT estimates for job finding at different time horizons for (a) males and (b) females. Sample restricted to job seekers who were still unemployed as of 19/11/2019. Standard errors are clustered at the labor market (Occ.*CZ) level and associated 95% confidence intervals are displayed.

The respective responses of males and females to our intervention differ markedly. In Figure 2, the overall response of men is around zero, while women's response after two months since the beginning of our intervention is positive and significant. In Section A.6 in the appendix, we investigate candidate explanations for such heterogeneity — e.g., differences in observable characteristics and differences in take-up rates. Overall, this differential effect between males and females does not seem to be driven by differences in observables. However, female job seekers seem to respond more to our encouragement — in the sense that they open our e-mails more frequently than their males counterparts.[19]

Driven by this observation, we investigate in Table 6 whether the effect is concentrated on hiring firms (BB), or if it also appears when considering job finding rates in other firms (not BB). Overall (panel A.), we observe that the effect seems to be driven by hirings in BB firms. Yet this hides some heterogeneity between males and females job seekers. Indeed, panel B. shows that the job finding rate of female job seekers increased significantly in non-BB firms.[20]. The effects observed for male job seekers are quite different, and suggest a very different reaction to our intervention. Indeed, the intervention appears to have redirected their search effort from non-BB firms to BB firms — as their job finding rate significantly decreased in the former, and significantly increased in the latter. This gender differential in behavior would explain a

[19]We also study the heterogeneity of our effect by contract types. Figure A9 in appendix A.6 shows that the effect on the job finding rate of female job seekers appear to be driven by an increase in the probability to find definite duration contracts.

[20]The effect of the treatment appears to be significant for non-BB firms, and not statistically different from 0 for BB firms. Yet at a percentage of the respective baselines, both effect seem to be of the same order of magnitude, between 1 and 2 percentage points of the baseline.

larger overall effect among women — mostly due to an increased (yet undirected) search effort. Meanwhile, male job seekers's search effort would have remained mostly unchanged overall, yet redirected by our e-mails towards BB firms — either due to our specific recommendations, or our general redirection towards the LBB platform.

In order to provide more evidence on this search behavior of men and women — and in particular, the ability (or not) of our intervention to redirect the search effort of one or the other — we study in the following section the impact of our intervention on the match probabilities of *specific recommendations*.

Table 6: ITT estimates, by type of firm

	(1) All firms	(2) Not BB	(3) BB
	A. All		
Treatment	0.000752	-0.000408	0.00116
	(0.000924)	(0.000774)	(0.000596)
Baseline	0.194	0.125	0.0693
	(0.00189)	(0.00143)	(0.000911)
Observations	800297	800297	800297
	B. Females		
Treatment	0.00265	0.00181	0.000835
	(0.00119)	(0.000947)	(0.000830)
Baseline	0.174	0.103	0.0708
	(0.00249)	(0.00172)	(0.00124)
Observations	439443	439443	439443
	C. Males		
Treatment	-0.00166	-0.00322	0.00156
	(0.00144)	(0.00125)	(0.000876)
Baseline	0.220	0.152	0.0675
	(0.00181)	(0.00147)	(0.00106)
Observations	360854	360854	360854

Notes: Standard errors clustered as the labor market (CZ $\times$ Occ.) level reported in parenthesis. Job finding rates displayed in the first column are decomposed into different categories of hiring, depending on the type of firm that made the hire. The coefficients displayed in the "Treatment" row are our ITT estimates, by type of firm. Column 1 reports the ITT estimate for all hiring. Column 2 (Not BB) focuses on firms that are not considered as "hiring firms" (i.e., their predicted hirings are not high enough according to LBB's algorithm). Column 3 (BB) focuses on hirings firms (BB), whether they were recommended or not to the job seeker.

VI.2 Impact on matches: disentangling activation and targeting effects

The results of the previous section suggest that the effect of our intervention on job finding rates is not entirely driven by our targeting device. Indeed, our treated job seekers have an increased likelihood to find a job in hiring firms (BB) even when those firms were not recommended to them in the e-mails. This is not entirely surprising as our intervention was designed in a way that could very well increase the overall search effort of job seekers. In particular, we encouraged the use of the LBB platform, possibly inducing an increase in the search effort of treated job seekers directed to *any* firms presented on the LBB platform.

Our two-sided randomization design allows us to disentangle these two components of our intervention — namely, an activation and a targeting effect — by taking the analysis to a finer scale, at the level of job seeker-firm pairs. The activation effect is defined as the increase in the likelihood that *any* match (job seeker i, hiring firm j) occurs when job seeker i is in the treated group, in the absence of any recommendation for the pair (i, j). This effect captures the overall (and non-targeted) increase in search effort among treated job seekers. Formally, if Y_i^j denotes the indicator for whether job seeker i was hired in firm j, Z_i indicates whether or not i is in the treated group, and R_i^j indicates whether the pair (i, j) has been recommended, the activation effect is defined as:[21]

$$\textbf{Activation effect} \equiv E\left[Y_i^j(Z_i = 1, R_i^j = 0) - Y_i^j(Z_i = 0, R_i^j = 0) | R_i^j = 1\right]$$

On the other hand, the targeting effect is defined as the impact on the likelihood that a given match (i, j) occurs if job seeker i is treated and firm j was recommended to her. Formally:[22]

$$\textbf{Targeting effect} \equiv E\left[Y_i^j(Z_i = 1, R_i^j = 1) - Y_i^j(Z_i = 1, R_i^j = 0) \mid R_i^j = 1\right]$$

Both quantities can be identified and estimated through re-weighting strategies, and by carefully defining the population and estimation sample, as described in appendix A.8. Indeed, whether a given pair (i, j) was recommended or not is not orthogonal to the potential outcomes $Y_i^j(Z_i = t, R_i^j = t)$. This is because our recommender system was designed such that (on average) it

[21] Notice that this effect is an average treatment on the *recommended* dyads of job seekers and firms (ATT). As far as the activation effect goes, the average treatment effect would also be a relevant quantity as dyads were in principle affected by this effect no matter their recommended status — as long as they were involving a treated job seeker. Yet in fact, one would expect that most of this activation effect occurs on dyads that *could have been recommended*. Indeed, job seekers would not search for *any* match when they increase their search effort. Instead, they might focus on a subset of match for which their baseline likelihood of success is relatively high — which is exactly what the set of potentially recommended dyads is.

[22] This is an average treatment effect on the *recommended* dyads (ATT). As far as the targeting goes, this is most relevant quantity to consider. Indeed, by construction only recommended dyads were affected by the targeting aspect of our intervention. And these dyads were not chosen independently from their potential outcomes with and without recommendations, hence the average treatment effect on the recommended dyads is likely to differ from the average treatment effect.

would give higher probabilities of recommendation to pairs with a higher baseline matching likelihood. Hence comparing recommended pairs with non-recommended pairs would not identify any causal effect. However, since we know those recommendation probabilities, we can re-weight non-recommended pairs so that their outcome distribution identifies the (potential) one of recommended pairs *had they been non-recommended*. This allows for the identification (and estimation, by the analogy principle) of the targeting effect. Similarly, the activation effect can be identified by comparing non-recommended pairs involving treated job seekers with non-recommended pairs involving control job seekers. We simply need to re-weight observations appropriately so that non-recommended pairs involving control job seekers match the distribution of non-recommended pairs involving treated ones, had the latter been control individuals.

We present the results of this exercise in Table 7. Overall, the targeting effect appears to be larger (in absolute terms) than the activation effect (column 1). It is also (marginally) significant, while the activation effect is not clearly distinguishable from 0 in our dataset. Moreover, the targeting effect appears to be driven by male job seekers while the activation effect is if anything larger among female job seekers (columns 2 and 3). This is in line with the evidence discussed in the previous section, in which we found that our intervention redirected the search effort of men towards BB firms to a larger extent than for women — whose search effort appeared to be increased overall (BB and non-BB firms). Interestingly, the targeting effect tends to be larger (relative to the baseline) at larger occupational distances (columns 4 and 5) — from 11.7% of the baseline (not significant) at zero occupational distance to 22.8% at occupational distance between 1 and 4 (marginally significant).

All of these observations combined are confirming the ability of our recommender system to redirect search effort of a least a subset of job seekers. More than that, it confirms that this tool was effective at redirecting search effort *outside* of one's own labor market. This last point is key for our purposes, as the main margin through which our intervention could generate social returns is its ability to generate balancing flows of labor force from slack to tight labor markets. This is only possible if the recommender system used proves to be able to generate such redirection of search effort, as the last two columns (4) and (5) of Table 7 suggest. Motivated by these encouraging results, the next section analyzes the effect of our intervention on labor market frictions — by studying the direct and indirect effects of reallocating search effort across (slack and tight) labor markets.

Table 7: Activation and targeting effects, by gender and occupational distance

	(1) All	(2) Men	(3) Women	(4) d = 0	(5) d > 0
			A. Targeting		
R	0.0000549	0.0000776	0.0000375	0.0000604	0.0000397
	(0.0000331)	(0.0000434)	(0.0000458)	(0.0000460)	(0.0000265)
	[0.10]	[0.07]	[0.41]	[0.19]	[0.13]
Baseline	0.0004252	0.0003146	0.0005100	0.0005157	0.0001738
N	48475273	18020081	30455192	23411284	25063989
			B. Activation		
R	0.0000417	0.0000166	0.0000609	0.0000428	0.0000374
	(0.0000356)	(0.0000516)	(0.0000497)	(0.0000470)	(0.0000281)
	[0.24]	[0.75]	[0.22]	[0.36]	[0.18]
Baseline	0.0003835	0.0002980	0.0004492	0.0004729	0.0001364
N	70466951	26004397	44462554	33453847	37013104

Notes: This table presents estimates of the targeting (A) and activation effects (B) of our intervention at the dyad level (i.e., a pair of job seeker i and firm j) on the probability that the match is actually realized. The activation effect is defined as the effect on the probability that any given match occurs when the job seeker involved in the match is treated. The targeting effect is the effect of recommending i to j on the probability that the match (i, j) occurs. Column (1) reports the overall targeting and activation effects in our sample. Columns (2) and (3) split these estimates by gender. Columns (3) and (5) split these estimates according to the occupational distance of the recommendation ($d = 0$ vs $d > 0$). Standard errors are clustered at the labor market level (CZ*occupations) and are reported in parentheses. Associated two sided p-values are reported in brackets.

VII Social returns to the reallocation intervention: direct and indirect effects

The results of the previous section show the potential of the LBB platform in terms of directing job seekers' search toward specific firms. Going beyond this proof of concept, we ask in this section whether this targeting effect can be used to influence the occupational scope of job search and, ultimately, to reduce congestion frictions and mismatch unemployment. As argued above, we believe this to be the key question from a policy perspective: can we in practice use recommender systems to reduce occupational mismatch, by redirecting job seekers' search toward tighter occupations? In this section, relying on Hu et al. (2022), we estimate the average direct and indirect (i.e., spillover) effects of redirecting job seekers from their occupations to neighboring ones. Ultimately, as described in section II and in Hu et al. (2022), these parameters identify a sufficient statistic for whether or not our reallocation intervention should be pushed further or not.

By reallocation intervention, we mean that our recommender algorithm generated recommendations to search in neighboring occupations when it seemed appropriate for social welfare — see section IV. For instance, job seekers in a given market m had higher chances of being recommended to apply to firms in market m' (in the same CZ, but in a neighboring occupation) if the tightness in market m was lower than in m' — see Table 5. Such suggestions of labor reallocation from slack to tight markets are made in the hope of reducing congestion frictions in slack markets while easing the matching process in tight markets. Yet at the end of the day, whether or not this led to a net social welfare gain — as measured by the overall job finding rate in the population of job seekers — remains an empirical question. It depends on both (i) the ability of the system to effectively redirect search effort, and (ii) the effect of such reallocation on the matching process in slack and tight markets.

As noted in section II and in Hu et al. (2022) it turns out that under our randomization design, one can identify key parameters to answer this question. As above, let W_i denote the indicator for whether we recommended to job seeker i any firm that was hiring in a neighboring market of i's one. Further define for any of the $i = 1, \ldots, n$ job seekers their potential outcome $Y_i(\mathbf{W}) \in \mathbb{R}$. This potential outcome is a function of the whole treatment vector $\mathbf{W} \in \{0,1\}^n$, that gives the treatment status of all n job seekers. This underlines the fact that at this stage, we allow for any pattern of interference across job seekers. The first parameter of interest is often called the average direct effect (ADE), and is defined as follows:

$$\mathrm{ADE} \equiv \frac{1}{n} \sum_{i=1}^{n} E\left[Y_i\left(W_i = 1; \mathbf{W_{-i}}\right) - Y_i\left(W_i = 0; \mathbf{W_{-i}}\right)\right]$$

This parameter measures the average effect of the redirection intervention W_i on the unit being intervened on — while marginalizing over the rest of the treatment assignments of other job seekers. In a setting without interference, the ADE would match the standard average treatment effect parameter. The Horvitz-Thompson estimator for the ADE parameter is given by:

$$\widehat{\text{ADE}} = \frac{1}{n}\sum_{i=1}^{n}\left\{\frac{W_i Y_i}{\pi_i} - \frac{(1-W_i)\,Y_i}{1-\pi_i}\right\},$$

where Y_i indicates whether or not i has find a job, and π_i gives the probability that W_i equals 1 — in other words, the reallocation probability for job seeker i. In our experiment, this probability is homogeneous for all job seekers belonging to the same market, and heterogeneous across markets — slack markets having higher π's than tight ones.

The second and less usual parameter of interest is the average indirect effect (AIE), formally defined as:

$$\text{AIE} \equiv \frac{1}{n}\sum_{i=1}^{n}\sum_{j\neq i} E\left\{Y_j\left(W_i = 1; \mathbf{W_{-i}}\right) - Y_j\left(W_i = 0; \mathbf{W_{-i}}\right)\right\},$$

This parameter measures the average effect of W_i on all units but the one being intervened on, again marginalizing over the rest of the treatment process $\mathbf{W_{-i}}$. In other words, it corresponds to the average of the effects of job seekers' treatments on all the other job seekers. As such, it quantifies the amount of spillover effects.[23] The Horvitz-Thompson estimator for the AIE parameter is given by:

$$\begin{aligned}\widehat{\text{AIE}} &= \frac{1}{n}\sum_{i=1}^{n}\sum_{\{j\neq i:E_{ij}=1\}}\left\{\frac{W_i Y_j}{\pi_i} - \frac{(1-W_i)\,Y_j}{1-\pi_i}\right\}\\ &= \frac{1}{n}\sum_{i=1}^{n}\left\{\left(\frac{W_i}{\pi_i} - \frac{(1-W_i)}{1-\pi_i}\right)\sum_{\{j\neq i:E_{ij}=1\}} Y_j\right\}\end{aligned}$$

where E_{ij} indicates whether job seeker i and j belong to the same interference space.[24] The key to our design's ability to identify and ultimately yield an unbiased estimator of τ_{AIE} is the independence of the treatment status draws across job seekers — see Hu et al. (2022) appendix for further details. As demonstrated in Hu et al. (2022) appendix, the Horvitz-Thompson estimator for AIE presented in the above display is unbiased in such Bernoulli-randomized experiments.

With this in mind, we can define different variants of the AIE parameter depending on (i) the spillover effects we are interested in and (ii) the extent of the interference space that we conjecture to be relevant. We study three AIE parameters here. The first, denoted AIE(0), is the average effect of reallocating i's search effort ($W_i = 1$) on the employment outcomes of all job seekers

[23] In the absence of any spillover effects, we have by construction $\text{AIE} = 0$.

[24] In other words, if $E_{ij} = 0$, it means that we can rule out *ex ante* that j's treatment status can affect i's outcome in any way.

belonging to i's original market. Formally:

$$\text{AIE}(0) \equiv \frac{1}{n}\sum_{i=1}^{n}\sum_{j\neq i:j\in m(i)} E\left\{Y_j\left(W_i=1;\mathbf{W_{-i}}\right)-Y_j\left(W_i=0;\mathbf{W_{-i}}\right)\right\}$$

$$\widehat{\text{AIE}(0)} = \frac{1}{n}\sum_{i=1}^{n}\left\{\left(\frac{W_i}{\pi_{m(i)}}-\frac{(1-W_i)}{1-\pi_{m(i)}}\right)\sum_{\{j\neq i:j\in m(i)\}} Y_j\right\}$$

where $m(i)$ denotes job seeker i's market. This is a key parameter as it captures the extent to which we reduce congestion frictions by redirecting search effort out of (slack) markets. On the flip side, this reallocated search effort tends to add congestion in relatively tighter markets toward which it is redirected. To measure this congestion effect, we define two additional AIE parameters, AIE(1) and AIE(2), given by:

$$\forall d\in\{1,2\},\ \text{AIE(d)} \equiv \frac{1}{n}\sum_{i=1}^{n}\sum_{j\neq i:j\in M(m(i)+d)} E\left\{Y_j\left(W_i=1;\mathbf{W_{-i}}\right)-Y_j\left(W_i=0;\mathbf{W_{-i}}\right)\right\}$$

$$\widehat{\text{AIE(d)}} = \frac{1}{n}\sum_{i=1}^{n}\left\{\left(\frac{W_i}{\pi_{m(i)}}-\frac{(1-W_i)}{1-\pi_{m(i)}}\right)\sum_{\{j\neq i:j\in M(m(i)+d)\}} Y_j\right\}$$

where $M(m(i)+d)$ is the set of markets at d steps of market $m(i)$ in the occupational graph we use. Therefore, these quantities capture the spillover effects of reallocating i's search effort $(W_i = 1)$ on the employment outcomes of all job seekers belonging to i's neighboring markets.[25] Since these are the markets in which i's search effort is redirected, we would also expect some interference to occur here. Yet in this case, we likely create some additional congestion instead of reducing them, hence we would expect some negative effect on average.

Table 8 reports estimates of all four parameters. Panel A presents the estimated effect on hiring outcome in any firm, while panel B reports the estimated effect on hiring in hiring firms (BB) specifically. The results are quite consistent across both cases. Firstly, we estimate that the ADE is very close to 0. This is interesting, as one could have feared we would deteriorate the labor market prospects of individuals encouraged to reallocate their search effort to neighboring markets. We interpret this 0 effect as implying that, from the job seeker's perspective, the cost of moving to a nearby occupation is offset by the fact that hiring prospects are better in this occupation (tighter local market). Meanwhile, the AIE(0) parameter is estimated to be strictly positive — and statistically different from 0 at the 90% level. We interpret this result as evidence that our efforts to reallocate labor out of slack markets did reduce congestion frictions to some extent in these markets. At the same time, we expect increased competition

[25]We restrict our attention to markets at 1 or 2 steps of i's market in the occupational graph as most of the recommendations outside of i's initial market were made toward these very close markets. As an indication, 48.9% of recommendations made in neighboring occupations were made toward markets at one step in the occupational graph.

for jobs in markets toward which we redirected job seekers. Hence we need to factor in the estimates for AIE(1) and AIE(2) in our analysis to determine whether or not our reallocation intervention creates net gains in social welfare. As expected, the estimates for AIE(1) turn out to be negative — or close to 0 in the case of panel B. Yet their magnitude appears to be smaller than the positive effect AIE(0). Given the noise with which we estimate AIE(1) — this variance issue is even more important for AIE(2) — it is difficult to draw definitive conclusions about the overall effect of the intervention. Yet point estimates suggest that the decongestion effect in slack markets dominate the counterbalancing effect of the additional competition created in tight markets, yielding net social benefits overall. These are encouraging results for such a recommender algorithm: it suggests that pushing (at least marginally) further its reallocation component might be beneficial. Indeed, as we saw in section II, Theorem 1 of Hu et al. (2022) states that, in a Bernoulli trial, a positive sum of ADE and AIE implies that increasing the share of job seekers being redirected increases aggregate welfare.[26] As can be seen in table9, this encouraging result is confirmed by the fact that the positive indirect effect that we find in column (2) of table 8 appears to be entirely driven by workers looking for a job in a slack labor market. This finding suggests that the positive indirect effect in a worker's own labor market is indeed linked to a decrease in search congestion effects on workers' side of the labor market.

[26]In theory, it is not obvious up to which occupational distance one should consider that interference effects occur. Despite the fact that most recommendations were made at an occupational distance of 1, it could very well be that redirecting toward these close markets has spillover effects on the labor market prospects of job seekers that are connected to these destination markets. Hence from one market to the next, redirecting job seeker i can affect most labor markets in a given CZ in theory. Yet in practice, it is likely that such spillover effects at high occupational distance are of second order, and there is no hope to estimate those accurately, hence our choice to focus on a relatively small but relevant perimeter for the interference space. We can already observe that AIE(2) is estimated with a lot of noise in Table 8, bringing little information about the spillover effects at such occupational distance.

Table 8: ADE and AIE of broadening job search on job finding rates, by occupational distance

	(1) ADE	(2) AIE(0)	(3) AIE(1)	(4) AIE(2)
	A. All firms			
W	-0.005	1.721	-0.319	-9.391
	(0.008)	(0.991)	(3.69)	(8.087)
	[0.516]	[0.082]	[0.931]	[0.246]
Observations	441,071	441,071	430,430	423,301
Nb. markets	19,511	19,511	18,152	18,383
	B. Hiring firms (BB)			
W	-0.002	0.206	0.039	-1.043
	(0.004)	(0.135)	(0.441)	(0.840)
	[0.543]	[0.129]	[0.929]	[0.214]
Observations	441,071	441,071	430,430	423,301
Nb. markets	19,511	19,511	18,152	18,383

Notes: Clustered standard errors at the local market level in parenthesis. P-values for the null hypothesis of a zero coefficient reported in brackets. Panel A presents the effects on the job finding rates in any firm, while panel B focuses on hiring in hiring firms only. The first column reports the average direct effect (ADE) of making at least one recommendation towards a neighboring occupation to a job seeker on its own job finding rate. The second column reports the average indirect effect (AIE) at an occupational distance of 0, i.e., the effect of making at least one recommendation towards a neighboring occupation to job seeker i on the *sum* of the job finding rates of job seekers belonging to the same local market as i. The third column report the effect on the sum of job finding rates of job seekers in job seeker i's neighboring markets (AIE(1)) — i.e., at an occupational distance of 1 from i. The fourth column reports the same coefficient for job seekers at an occupational distance of 2 from job seeker i.

Table 9: AIE of broadening job search on job finding rates at distance 0, by local tightness

	(1) Slack	(2) Tight	(3) Slack	(4) Tight
	A. All firms		B. Hiring firms (BB)	
W	3.0272	0.4693	0.2918	0.1230
	(1.7890)	(0.9992)	(0.2087)	(0.1815)
	[0.09]	[0.64]	[0.16]	[0.50]
Observations	215934	225137	215934	225137

Notes: Clustered standard errors at the local market level in parenthesis. P-values for the null hypothesis of a zero coefficient reported in brackets. Panel *A* presents the effects on the job finding rates in any firm, while panel *B* focuses on hiring in hiring firms only. Fore each type of hiring firm, this table splits the Average Indirect Effect at occupational distance 0 (AIE(0)) presented in column (2) of table 8 by above/below median tightness of job seekers' origin market. Local labor market tightness is defined as the ratio of total predicted hirings to the number of job seekers.

VIII Conclusion

Building upon an existing job search platform operated by the French PES, we show that recommender systems have the potential to increase aggregate employment by redirecting job seekers toward tighter occupations. This reduction in occupational mismatch comes on top of a more standard activation effect, by which recommending job seekers to make unsolicited applications to firms increases their overall search effort.

Our study uses an encouragement design, e-mailing treated job seekers. Such designs typically have limited take-up, and our study is no exception. In that context, the large scale of the experiment is key for two reasons. First, it allows us to detect small effects with sufficient precision, a decisive feature when it comes to assessing indirect effects that are typically hard to estimate. Second, it shows that a realistic, low-cost intervention, can have real-life effects. It remains however the case that effects are small, when expressed in terms of job finding rates. While this does not prevent the policy to be very likely cost effective (given its very low cost), it begs the question of whether features of the intervention could be enhanced to increase impact. In that respect, how to make redirection suggestions salient at scale, in the typical search environment faced by job seekers — for instance by integrating to widely used platforms such tools as those developed in a more controlled environment by Belot et al. (2018b) — remains an important avenue for future research.

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A Appendix

A.1 Context

Figure A1: LBB's home page

Figure A2: LBB's research results page

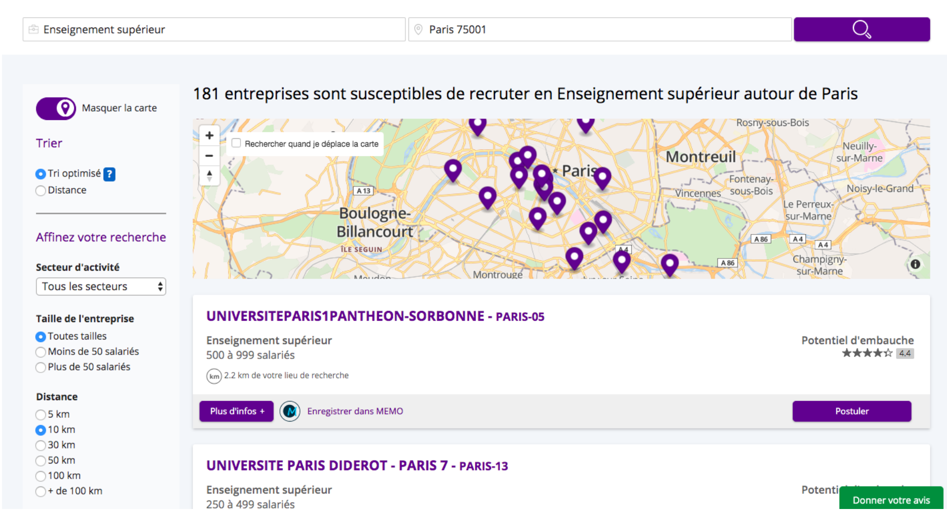


Figure A3: LBB's Firm contact information page

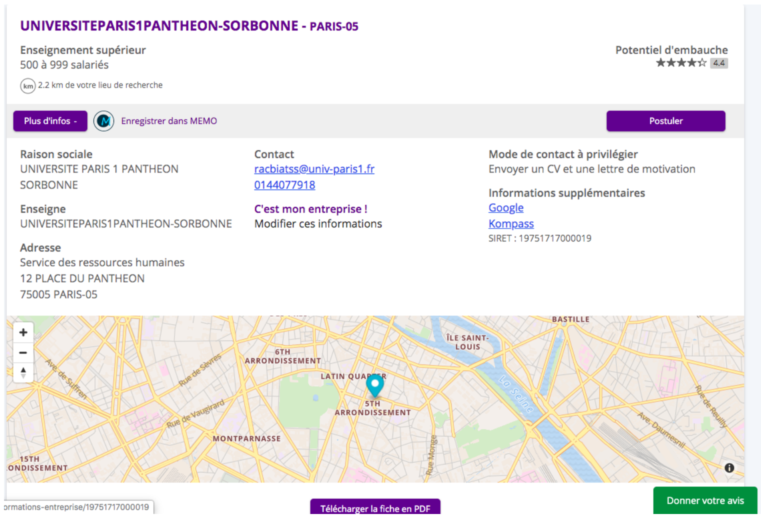


Figure A4: Email sent to treated job seekers

Bonjour M. Zuber,

Vous êtes inscrit à Pôle emploi et avez déclaré rechercher un emploi dans la catégorie : « Sommellerie ».

Savez-vous que 7 entreprises sur 10 examinent des candidatures spontanées avant de se décider à publier une offre d'emploi ?

La Bonne Boite, un service de Pôle emploi, a repéré des entreprises que votre profil pourrait intéresser.

En voici une susceptible de rechercher un profil proche du vôtre :

- GSF MERCURE

Vous pouvez leur envoyer une candidature spontanée.

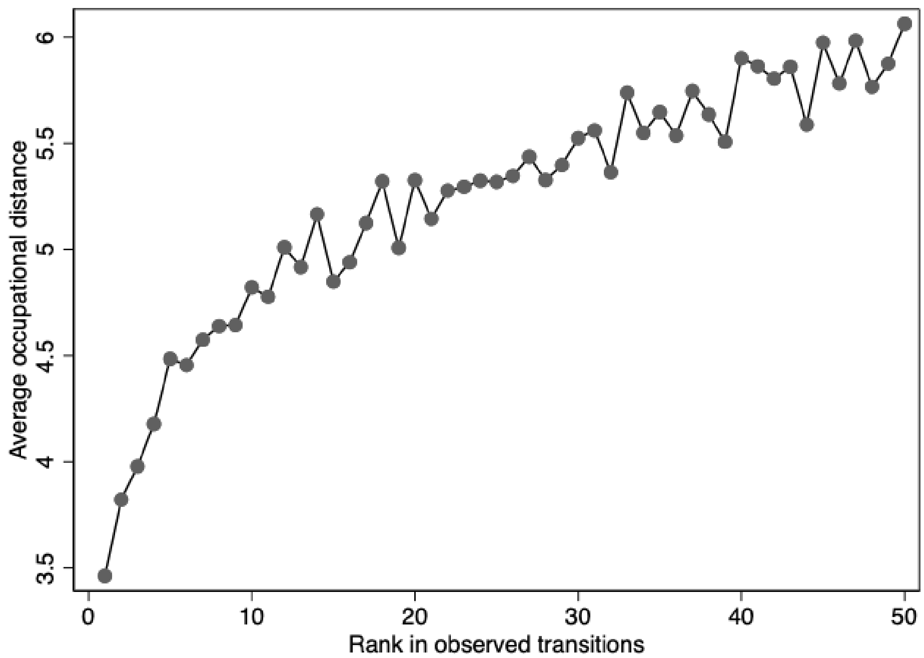
En cliquant sur ce lien, vous pourrez contacter l'entreprise grâce aux coordonnées qui s'affichent ou en utilisant l'outil de candidature en ligne **« postuler »** lorsque celui-ci est disponible.

Vous avez également la possibilité de retrouver d'autres entreprises sur le site La Bonne Boite

En vous souhaitant une pleine réussite dans votre recherche d'emploi.

A.2 Occupational distance and observed transitions

Figure A5: Mean occupation distance vs observed rank in occupational transitions



Note: This graph constructed by ranking occupational transitions according to their frequency within each origin occupation and then computing the mean occupational distance of these transition in each rank category. In other words, across all origin occupations, destination occupation ranked first in terms of transitions were located at an average occupational distance of 3.5. Data on occupational transitions are constructed from the FHDADS panel covering the 2008-2012 period. We are constrained to this rather short period because prior to 2008 the DADS did not record a 4-digit occupation. An occupational transition from A to B is defined as a job seeker looking for a job in occupation A finding a job in occupation B. While the search occupation A is coded in the ROME classification, the destination occupation B is coded according to the PCS classification used in DADS files. We translate the PCS classification into the ROME one by using the ROME-FAP-PCS matching provided by the French unemployment agency as well as each ROME's distribution of educational attainments among job seekers observed in our pre-treatment data. In total this graph is constructed from 1,092,233 individual transitions over the 2008-2012 period

A.3 Commuting zones and local labor markets

A.3.1 Commuting Zones

For administrative purposes the PES divides the french territory into 404 commuting zones ("bassins d'emploi"). A commuting zone is a geographical space where most of the population lives and works. In other words, most people do not leave this area to go to their place of work. Both job seekers and firms are thus mapped to an specific commuting zone through their zip code. These areas have an average population of $160,000$ and are spread over an average radius of 20.3km.[27] Finally, and consistent with France's unemployment rate, there are on average $13,467$ job seekers in each commuting zone.

For this experiment 94 commuting zones out of the 404 initial ones were selected. We leave the 310 remaining commuting zones untouched for a future experiment guided by the learnings of this one. Nevertheless this experiment remains a large-scale experiment with more than 1.2 million job seekers and 750 thousand firms involved. The 94 commuting zones of our interest are randomly selected from the pool of commuting zones. Table A1 shows the main characteristics of commuting zones selected for the experiment (column 1) and commuting zones not selected for the experiment (column 2). We observe that characteristics between those groups are balanced and therefore our sample is representative of the entire France.

Table A1: Commuting Zones' statistics

	(1)	(2)	(3)
Variable	Selected Zone	Non Selected Zone	(2)-(1)
Surface (m2)	182507.453	150871.219	-31636.240
	(423423.031)	(200091.297)	(31,679.127)
Population	154650.000	161688.672	7,038.673
	(133044.750)	(196349.313)	(21,628.875)
Number of Unemployed	12,870.830	13,648.951	778.122
	(12,109.896)	(17,855.393)	(1,966.694)
Unemployment Ratio	0.079	0.081	0.002
	(0.017)	(0.019)	(0.002)
Number of Hiring Firms	7,985.681	8,512.371	526.690
	(9,362.619)	(15,645.074)	(1,699.878)
Tightness	0.623	0.585	-0.038
	(0.402)	(0.241)	(0.034)
Observations	94	310	404

Standard errors in parenthesis.

[27] We miss data for one commuting zone which regroups Saint-Martin and Saint-Barthélémy.

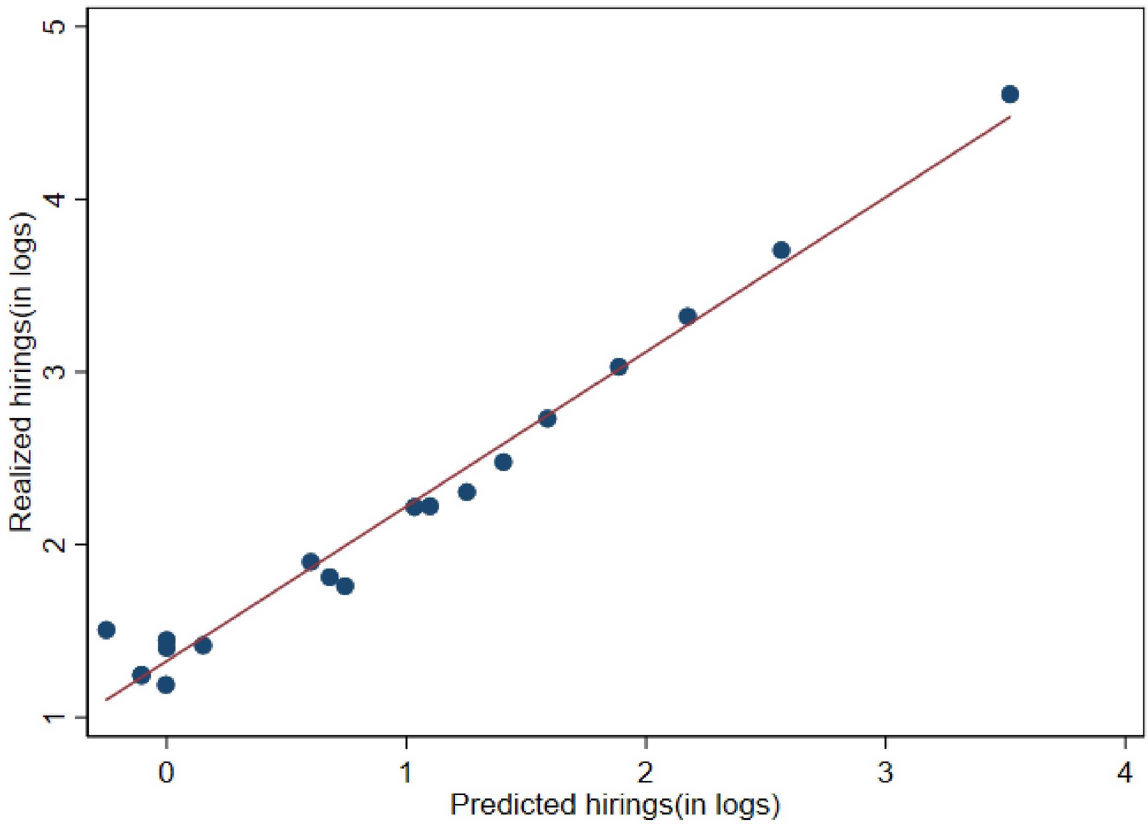
A.3.2 Local Labor Markets

Upon registrating with public employment services, job seekers are asked to fill in a certain number of personal information including their desired occupation. As one's desired occupation is not, however, a required information we drop job seekers whose search occupation appears as missing in our data. Job seekers who choose to register a desired occupation can select one occupation from the 532 options given in the "ROME" classification of occupations used by french unemployment services[28]). We define a local labor market as the intersection between commuting zones and occupations. In France there are 404 CZ ands 532 occupations, which makes $404 \times 532 = 214928$ local labor markets. Among these potential labor market only 174733 turn up with a least one job seeker or one active establishment. On average a local labor market is populated by 31 job seekers and 19 establishments which total 12 predicted hirings. The mean predicted hirings to job seekers ratio is 0.31. This ratio can be thought of as the predicted tightness of our local labor markets.

[28] ROME stands for "Répertoire opérationnel des métiers": Operational directory of occupations.

A.4 Correlating predicted and realized hirings

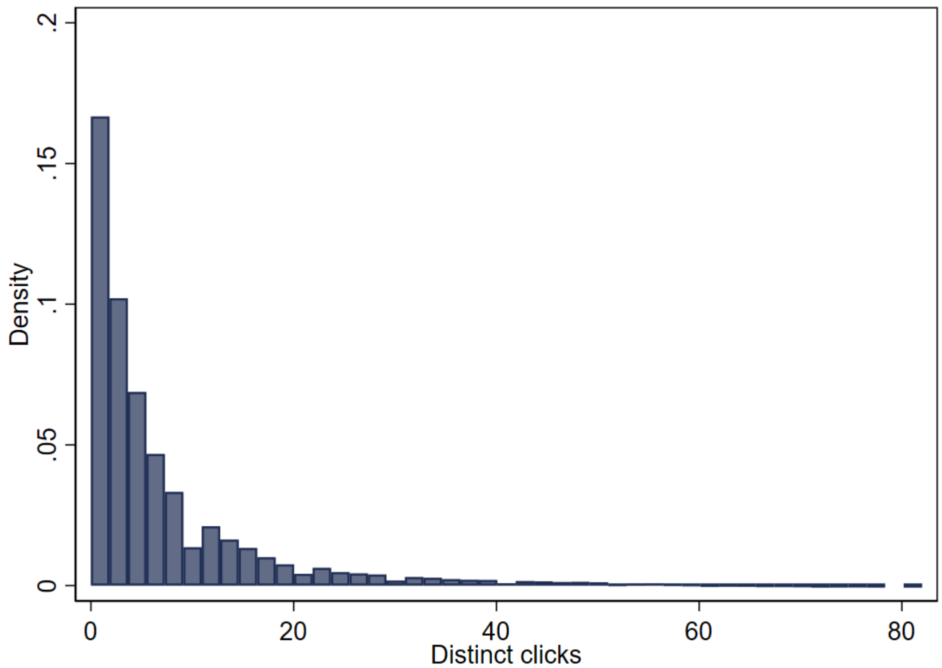
Figure A6: Realized hirings among unemployed job seekers over the 30/09/2019-13/03/2020 period vs LBB's predicted hirings as of 11/08/2019 (in logs)



Note: Correlation of the number of predicted hirings per establishment and the number of realized hirings. log(Realized hirings) = 1.33(0.0053) + 0.89(0.0039) × log(Predicted hirings), $R^2 = 0.37$

A.5 Ex-post treatment

Figure A7: Number of distinct clicks by treated establishment



Note: Distribution of the number of distinct clicks (one per job seeker) per establishment. The displayed distribution is cut above the 99th percentile. The average number of distinct clicks per establishment is 9.1

Table A2: Overall number of clicks for establishments in commuting zones where 60% of firms were treated

	(1) Pre intervention	(2) During intervention	(3) Post intervention
ITT	0.0124	1.539	0.0211
	(0.0908)	(0.0761)	(0.0547)
Constant	3.912	1.590	1.864
	(0.143)	(0.0635)	(0.0751)
N	47305	47305	47305
Mean	3.920	2.516	1.877
Adjusted R^2	-0.0000208	0.0100	-0.0000182

Note: ITT of the overall number of clicks for establishments in commuting zones with a 60% treatment rate during (1) the pre-intervention period, (2) while the intervention is going on and (3) in the month following the end of our intervention. Regressions are weighted by inverse treatment status probability. Standard errors are clustered at the labor market (Sector*CZ) level.

Table A3: Overall number of clicks for establishments in commuting zones where 20% of firms were treated

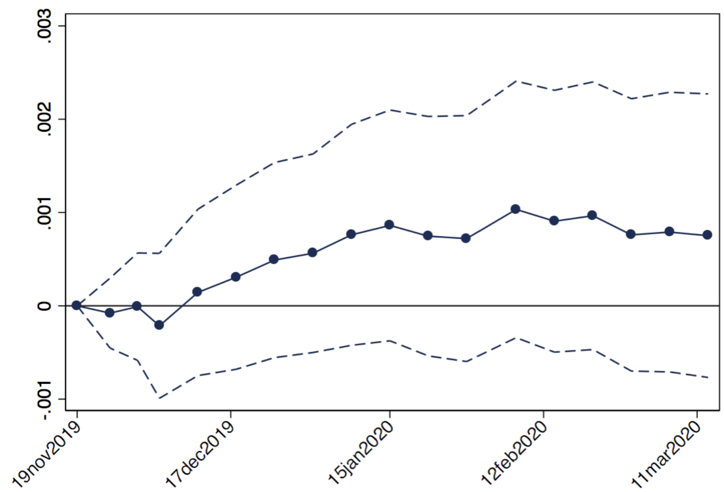
	(1) Pre intervention	(2) During intervention	(3) Post intervention
ITT	0.0221	2.044	0.0820
	(0.114)	(0.114)	(0.0601)
Constant	3.311	1.539	1.548
	(0.0849)	(0.0422)	(0.0399)
N	51061	51061	51061
Mean	3.315	1.951	1.565
Adjusted R^2	-0.0000185	0.0206	0.0000337

Standard errors in parentheses

Note: ITT of the overall number of clicks for establishments in commuting zones with a 20% treatment rate during (1) the pre-intervention period, (2) while the intervention is going on and (3) in the month following the end of our intervention. Regressions are weighted by inverse treatment status probability. Standard errors are clustered at the labor market (Sector*CZ) level.

A.6 Additional results on private returns

Figure A8: Job-finding rate ITT estimates

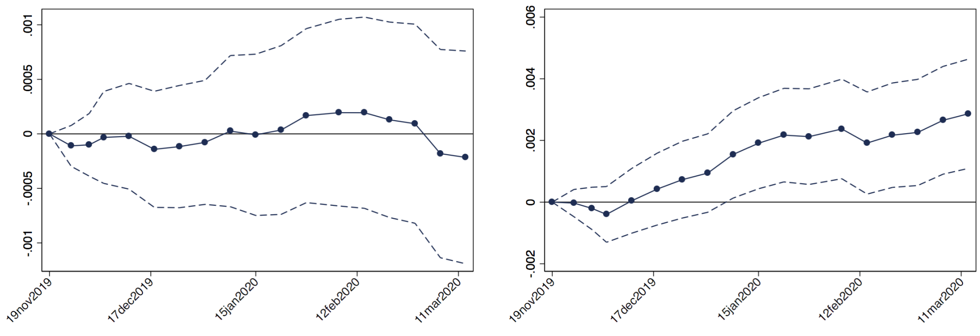


Note: This graph presents the ITT estimates for job finding at different time horizons. Sample restricted to job seekers who were still unemployed as of 19/11/2019. Standard errors are clustered at the labor market (Occ.*CZ) level and associated 95% confidence intervals are displayed.

Further decomposing women's response into access to indefinite as opposed to definite duration employment (Figure A9), we find that the positive effect of our intervention is driven by a rise in treated women's return to definite duration employment.[29]

[29] A further decomposition between "long term" (i.e. more than six months) definite duration contracts and short term (i.e. less than six months) definite duration contracts shows that this effect is driven by short term definite duration contracts.

Figure A9: Job-finding ITT estimates by contract type for females



(a) Indefinite duration (b) Finite duration

Note: ITT estimates for job finding of (a) indefinite duration and (b) finite duration contracts at different time horizons. Sample restricted to female job seekers who were still unemployed as of 19/11/2019. Standard errors are clustered at the labor market (Occ.*CZ) level and associated 95% confidence intervals are displayed.

Potential mechanisms underlying gender differences

Differences in observable characteristics

Women's and men's responses to tailored job-search advice appear to be strikingly different. Could this difference be driven unbalances in the gender distribution across observables and labor markets? In other words, are women reacting more to our treatment because they differ in some observable way from men or because they work in occupations that tend to respond more strongly to the provision of tailored job-search advice. To check this, we interact our intention-to-treat status with a male/female dummy and control for the interaction of our treatment with a set of observables, including a full set of labor market fixed effects. We present the results of these robustness checks for definite duration hirings in Table A4. The different response of men and women stays remarkably robust for all the interacted controls and interacted labor market fixed effects we include, indicating that the gender differences in the response to our provision of tailored job search recommendations do not appear to be driven either by individual level observables being correlated to gender differences or by labor market differences.

Table A4: Robustness check: do differences in observables explain treatment effect heterogeneity across gender

	(1)	(2)	(3)
Male # ITT	-0.0420	-0.0367	-0.221
	(0.135)	(0.135)	(0.149)
Female # ITT	0.287	0.309	0.257
	(0.108)	(0.110)	(0.130)
Controls	No	Yes	Yes
Labor Market FE	No	No	Yes
Observations	800297	800237	793103
Mean	0.154	0.154	0.154
Adjusted R2	0.00201	0.0203	0.109

Note: This table displays the results of a regression of finite duration job-finding on the interactions of our treatment with a dummy for males and a dummy for females. Column (1) does not add any control, column (2) controls for the direct and interacted effects of the centered value of age, a diploma dummy, experience and unemployment spell duration. Finally column (3) adds the direct and interacted effect of centered labor market (Occ.*CZ) fixed effects calculated through a first stage regression. Sample restricted to job seekers who were still unemployed as of 19/11/2019. Standard errors in parentheses are clustered at the labor market (Occ.*CZ) level. Coefficients and standard errors in percentage points.

Differences in take-up

To further investigate the gender differences in job seekers' responses to our intervention we try to follow gender differences along the causal chain that eventually links our intervention to the hiring of a job seeker. This causal chain starts with opening of emails, then goes on with clicking on links, applying to firms, being called for an interview, receiving an offer, accepting it. We start from the beginning by first looking at gender differences in initial take-up measures. To do so we regress our main take-up measures, opening at least one email and clicking on at least one link, on a male/female dummy. Table A5 shows that men are 6% less likely to open the emails we sent them. This big difference in take-up passes through to subsequent clicks and remains large when we include detailed individual level controls as well as labor market fixed effects. The fact that women are 25% more likely than men to click on the recommendation link we sent them cannot, however, fully account for the gender differential we see on final outcomes. The initial variation in take-up must hence be complemented by other differences involving latter stages of the hiring process. Unfortunately we were not able to track applications and interviews of all treated and control job seekers. One possibility could for instance be that men and women react differently to suggestions to widen the occupational breadth of their job-search effort — we investigate this possibility in the following subsection exploiting our web survey.

Table A5: Gender differences in take-up (in percentage points)

	Opened email			Clicked on link		
	(1)	(2)	(3)	(4)	(5)	(6)
Male	-6.733	-6.645	-3.982	-5.957	-5.796	-3.458
	(0.294)	(0.250)	(0.189)	(0.258)	(0.253)	(0.174)
Controls		Yes	Yes		Yes	Yes
Fixed effects			Yes			Yes
N	533557	533557	525702	533557	533557	525702
Mean	0.639	0.639	0.639	0.245	0.245	0.245

Standard errors in parentheses

Note: Regression of (1,2,3) opening at least one email and (4,5,6) clicking on at least one link on male female dummy. We add individual level controls in columns (3,4,5,6) as well as labor market fixed effects in columns (3,6). Sample restricted to treated job seekers who were still unemployed as of 19/11/2019. Standard errors are clustered at the labor market (Occ.*CZ) level. Coefficients and standard errors in percentage points.

A.7 Choice of the screening technology:

More specifically we choose to parametrize our screening function q^j as:

$$q_j(\theta^j) = \frac{1}{[1 + (\frac{\theta^j}{\Gamma m_j \bar{\theta}_j})^\gamma]^{1/\gamma}}$$

where $\gamma > 1$ and Γ are constants verifying:

$$\Gamma = (\frac{\gamma - 1}{2})^{-1/\gamma}$$

where m_j is a firm specific constant which interpret as screening effeiciency parameter, and where $\bar{\theta}_j$ denotes the local slackness ratio in firm j's hiring occupations. This local slackness ratio is defined as the ratio of possible recommendations present in the neighborhood of firm j to the total number of hirings predicted in firm's j hiring occupations. Formally:

$$\bar{\theta}_j = \frac{\sum_i \rho_i^{d_{i,j}} N_i}{\sum_h V^{j,h}}$$

For $\gamma > 1$ this function is monotonous in $\theta^j = A^j/V^j > 0$ and verifies:

$$q^j(0) = 1$$

$$q^j(+\infty) = 0$$

What's more q^j has an inflection point at $m_j\theta_j$ so that according to the value of m_j, firm's j congestion effect will start to quick in either before ($m_j = m_j^L < 1$) or after ($m_j = m_j^H > 1$) the number of recommendations sent to j relative to its predicted hirings (i.e A^j/V^j) reaches the local slackness ratio θ_j. In practice we select $m^L = 0.5$, $m^H = 1.5$ and $\gamma = 3$.

A.8 Estimation of targeting and activation effects

Recall that the parameters we are interested in are the following. The activation effect is then defined as the increase in the likelihood that *any* match (job seeker i, hiring firm j) occurs when job seeker i is in the treated group, in the absence of any recommendation for the pair (i, j). It captures the overall (and non-targeted) increase in search effort among treated job seekers. Formally, if Y_i^j denotes the indicator for whether job seeker i was hired in firm j, Z_i indicates whether or not i is in the treated group, and R_i^j indicates whether the pair (i, j) has been recommended, the activation effect is defined as:

$$\textbf{Activation effect } (ACT) \equiv E\left[Y_i^j(Z_i = 1, R_i^j = 0) - Y_i^j(Z_i = 0, R_i^j = 0)\right]$$

In the core of the paper, we focus on the activation effect on *recommended* dyads, which is defined as follows:

$$\textbf{Activation effect on rec. dyads } (ACT^{R=1}) \equiv E\left[Y_i^j(Z_i = 1, R_i^j = 0) - Y_i^j(Z_i = 0, R_i^j = 0)|R_i^j = 1\right]$$

On the other hand, the targeting effect is defined as the impact on the likelihood that a given match (i, j) occurs if job seeker i is treated and firm j was recommended to her. Formally:

$$\textbf{Targeting effect } (TARG) \equiv E\left[Y_i^j(Z_i = 1, R_i^j = 1) - Y_i^j(Z_i = 1, R_i^j = 0) \mid R_i^j = 1\right]$$

All the above quantities can be estimated as follows. For the overall activation effect (ACT), we consider the sample of (i) all dyads involving a control job seeker, and (ii) dyads involving a treated job seekers *and* that were not recommended. Then, we estimate ACT as follows:

$$\widehat{ACT} = \frac{1}{|D_{(Z_i=1,R_i^j=0)}|} \sum_{(i,j)\in D_{(Z_i=1,R_i^j=0)}} \left\{\frac{Y_i^j}{1-p_{ij}}\right\} - \frac{1}{|D_{(Z_i=0)}|} \sum_{(i,j)\in D_{(Z_i=0)}} \left\{Y_i^j\right\}$$

where $D_{(Z_i=z,R_i^j=r)}$ is the set of dyads where the job seeker has treatment status z, and the dyad (i,j) has recommendation status r. And we have used $p_{ij} \equiv \Pr[R_i^j = 1|X_i, X_j]$, which is the theoretical probability that dyad (i,j) is recommended conditional on the observable characteristics of the i and j. This can be backed out from our recommendation algorithm.

For the activation effect on the recommended dyads ($ACT^{R=1}$), presented in the core of the paper, we take the same sample as for ACT but the re-weighting scheme changes. We draw fake recommendation statuses for dyads involving control job seekers. We then estimate using the following estimator:

$$
\begin{aligned}
\widehat{ACT^{R=1}} =& \frac{1}{|D_{(Z_i=1,R_i^j=0)}|} \sum_{(i,j)\in D_{(Z_i=1,R_i^j=0)}} \left\{ \frac{1-\bar{p}_{Z=1}}{\bar{p}_{Z=1}} \frac{p_{ij}}{1-p_{ij}} Y_i^j \right\} \\
& - \frac{1}{|D_{(Z_i=0)}|} \sum_{(i,j)\in D_{(Z_i=0)}} \left\{ R_i^j Y_i^j + (1-R_i^j) \frac{1-\bar{p}_{Z=0}}{\bar{p}_{Z=0}} \frac{p_{ij}}{1-p_{ij}} Y_i^j \right\}
\end{aligned}
$$

where $\bar{p}_{Z=z}$ denotes the empirical probability that a given dyad is recommended among dyads involving job seekers with treatment status $Z = z$.

Lastly, we estimate the targeting effect on the recommended dyads, $TARG$, by taking the sample of recommended dyads and computing the following estimator:

$$
\begin{aligned}
\widehat{TARG} =& \frac{1}{|D_{(Z_i=1,R_i^j=1)}|} \sum_{(i,j)\in D_{(Z_i=1,R_i^j=1)}} \left\{ Y_i^j \right\} \\
& - \frac{1}{|D_{(Z_i=1,R_i^j=0)}|} \sum_{(i,j)\in D_{(Z_i=1,R_i^j=0)}} \left\{ \frac{1-\bar{p}_{Z=1}}{\bar{p}_{Z=1}} \frac{p_{ij}}{1-p_{ij}} Y_i^j \right\}
\end{aligned}
$$