From Hidden Skills to Opportunities: Benefits of the use of online job platforms *

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Abstract

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1 Introduction

The development of massive online platforms, for instance by private actors such as LinkedIn or Monster, promises to reduce asymmetries of information between labor supply and demand. Such platforms may form a welcome addition to the toolbox of Public Employment Services (PES) in their missions of easing matching on the labor market. However, the actual impact of these platforms on employment outcomes and the underlying mechanisms at work remain unclear.

In this paper, we propose to investigate the benefits of the use of digital matching platform. In partnership with the French Public Employment Service, Pôle emploi, we encourage randomly selected registered jobseekers to fill-in and publish their profile on the PES platform making them more visible to recruiters. We are able to track the effects of the intervention on a variety of outcomes, including employment, through rich administrative data and web logs provided by the French Employment Service

Intention-to-treat treatment effects are positive but non-significant for all types of employment outcomes in the full sample. However, these findings hide strong heterogeneity of the treatment effect within our population.

We contribute to research on the impact of digital job platforms on the matching process between recruiters and jobseekers. Two experimental work are close in design to ours because they leverage low cost intervention. Jones and Sen 2022 evaluate the effect of encouraging young graduates to register on digital employment platforms in Mozambique. They find no impact on average of using the platforms on employment-related outcomes, but a positive one on the subgroup of females with manual qualification. Kelley et al. (2022) examine labor market outcomes as well as beliefs changes of vocational training graduates randomly selected to be registered on a job portal and sent information about job vacancies. The intervention seem to have increased voluntary unemployment through an increase in the reservation wages of treated graduates, reducing employment outcomes. Most experimental work undertaken take place in developing countries and on particular samples (young graduates). Our study takes place in a very different labor market with a population representative of jobseekers in a developed country where baseline labor market frictions should be lower and where the government intervenes more in the market. Our sample of 252, 000 jobseekers has been randomly selected from the entire population of registered jobseekers in France and is diverse both in terms of occupation coverage and employability.

Other experimental work related to the impact of job portals leverage more intensive intervention. In South Africa, Wheeler et al. 2022 show that training young jobseekers on how to use LinkedIn positively impacts employment. Information provision to potential employers and jobseekers seems to be the main channel explaining those impacts. In our study we benefit from the rich amount of data gathered by the PES about a broad set of indicators. This allowed us to track the behavior of jobseekers, recruiters, and caseworkers, as well as obtain detailed information about labor market outcomes. Since our experiment was conducted within the framework of a PES, our results are directly relevant for employment policies.

This paper also adds to experimental work studying the impact of more general interventions to reduce informational frictions on the labor market. Recent work have been studying interventions aiming at reducing screening costs through different tools such as reference letters **?** or skills tests Carranza et al. (2021), Bassi and Nansamba (2018). On the supply side, Belot et al. (2018) show that giving personalized advice leveraging on new technologies broadens the set of jobs jobseeker are willing to consider, increasing the number of interviews passed. **?**

The rest of the paper is organized as follows: Section 2 discusses the context; Section 3 details the field experiment; Section 4 discusses our results on employment and explore heterogeneity dimensions; Section 5 gives clue on the potential impact channel through the analysis of intermediary outcomes ; Section 6 concludes.

2 Context and intervention

The French Public Employment Agency, Pôle emploi, is responsible for facilitating matching between jobseekers and employers at the national level. It supports jobseekers in finding employment and assists firms in recruiting suitable candidates. In addition to this support mission, Pôle emploi is also responsible for distributing unemployment benefits and monitoring jobseekers.

In parallel with the rise of private platforms such as LinkedIn, Pôle emploi has modernized its services and increasingly moved them online, sometimes relying on private initiatives **?**. To adapt to a changing labor market that values transversal skills, the institution has implemented a placement strategy prioritizing skills over jobs especially for jobseekers undergoing career transitions. This means it focuses on the skills job seekers possess and how those skills can be valued in the labor market. In 2018, Pôle emploi created its own profile platform to enable job seekers to signal their aptitudes online.[1]

Similar to private platforms, this profile platform enables jobseekers to create a profile that describes their work experiences, education, skills, and interests. Unlike a regular resume, the profile encourages jobseekers to list and provide details about both hard and soft skills they possess. This can also include specific examples of how they have applied their skills in previous roles through the upload of samples of their work as well as additional training or certifications they have earned. Once published, this information is visible to recruiters browsing the platform. The platform is open to anyone who wishes to create a profile and be visible to recruiters in the bank and not only to registered jobseekers. If the individual is registered at the PES, the profile may also be viewed by caseworkers and used by the institution to personalize services, such as job ad recommendations.

If published, the profile appears on a profile search engine accessible to recruiters. Recruiters can look for candidates by keywords, profession titles, and geographic regions. Furthermore, recruiters can filter their search results based on the type of degree or contract sought by the candidate, allowing for greater precision. Once a search is launched, recruiters are presented with a list of profiles each summarized in the form of a card. These cards display the candidate's most relevant information, including their title, description, and most important skills. Recruiters can then click on a profile to access more details about a candidate's education, work experience, and skills. Finally, recruiters can easily reach out to candidates by clicking on a "contact by email" button or adding them to their list of potential candidates. We provide images of the search engine, the summary card and a plain profile in Appendix A, Images 6, 7 and 8. Note that the search engine orders candidate that match a given query by default according to the last modification of their profile. This feature is important for interpreting the impact of our intervention. By incentivizing candidates to modify or update their profile, we move them up on the list of profiles.

Jobseekers are introduced to the service when they register and during their first interview with their assigned caseworker. However, they often do not use it for their job search. In our sample only 20% of jobseekers have a published profile at the PES at baseline. Reasons for this low engagement might be diverse and are detailed in .

It is important to bear in mind that unlike other well-known job platforms, it does not have the features of a social network and profiles of other candidates cannot be seen by jobseekers.

[1] A bank of "paper" resumes (i.e. the opportunity for jobseekers to upload non-standardized resumes) was already available before the creation of a profile.

2.1 Intervention

3 Experimental Design and Data

3.1 Sample

For 7 weeks, we sampled 36,000 jobseekers from our eligible population of jobseekers. At each round, we consider eligible jobseekers individuals who (1) are registered with the French Employment Service ; (2) reside in metropolitan France; (3) have an email ocntact ; (4) have consented to receive emails from the PES[2]. Our sample includes both jobseekers with existing profiles and those without. We split this sample into a control group of size 24,000 and a treatment group of size 12,000[3]. The treatment group received one email about the profile. At the end of the experiment we therefore observe 252,000 jobseekers, one-third of them having received an email incentivizing them to fill-in their profile.

Table ?? provides information about demographic and job related characteristics of jobseekers in our sample. The most represented level of qualification is qualified employees that represent 49% of the population and 63% are part of the first category which includes jobseekers who do not have any professionnal activity (Category 1)[4]. Most represented targeted sectors are ; Sales and Retail, Business support and Services to individuals and communities. On average, they made 1.5 visits to the PES website in the last month and had 1.3 meetings with their assigned caseworker in the last 3 months.

We are balanced across most variables at baseline, though variables related to contract preferences demonstrate statistical imbalance.

[2]At each batch, the amount of jobseekers we had to exclude for technical reasons represents on average 8% of the overall population of jobseekers which represents on average 6 500 000 individuals

[3]The experiment started on the 10th of January 2023 and ended on the 28th of February

[4]Jobseekers in the first three categories are required to be actively seeking work. This means keeping in regular contact with Pôle Emploi, updating their details every month and responding to job offers. If people in categories 1, 2 and 3 do not demonstrate that they are actively seeking work, they may be removed from the list or have their ARE payments reduced and then stopped. Category 1 refers to jobseekers have not worked the last month; Category 2 includes all persons who are actively seeking a job and who have xorked less than 78 hours the last month; Category 3 represents jobseekers who have worked more than 78 hours in the last month. The last two categories are exempt from job search. Category 4 includes jobseekers who are not available for work (training, illness) and finally category 5 includes people who are in full-time or part-time employment but have decided to remain registered in order to benefit from PES services.

Table 1: Sample characteristics

	Control mean	Treated mean	p-value
Male	0.490	0.487	0.111
Age	39.830	39.868	0.541
Number of days since registration	574.051	576.546	0.602
Already published a profile	0.211	0.214	0.114
Full time	0.790	0.786	0.003***
Permanent contract	0.684	0.682	0.026**
Years of experience	5.700	5.700	0.983
# website visits in the last month	1.461	1.445	0.243
# meeting with the caseworker in the last 3 months	1.288	1.293	0.762
Administrative category			
Category 1	0.633	0.632	0.586
Category 2	0.096	0.097	0.310
Category 3	0.172	0.172	0.801
Category 4	0.036	0.036	0.383
Category 5	0.063	0.063	0.958
Target job sector			
Agriculture	0.042	0.043	0.277
Arts and Crafts	0.008	0.008	0.477
Banking, Insurance and Real Estate	0.016	0.016	0.479
Sales and Retail	0.140	0.138	0.204
Communication	0.025	0.025	0.374
Construction	0.071	0.073	0.266
Hotel, Restaurant, Tourism	0.086	0.085	0.501
Industry	0.067	0.065	0.044**
Installation and Maintenance	0.037	0.037	0.722
Health	0.035	0.035	0.932
Services to individuals and communities	0.190	0.194	0.009***
Arts and Entertainment	0.030	0.030	0.942
Business support	0.137	0.136	0.465
Transports and logistics	0.100	0.101	0.227
Highest diploma's level			
Others	0.153	0.153	0.222
University degree	0.326	0.326	0.865
End-of-high-school diploma	0.231	0.231	0.607
Vocational degree	0.290	0.290	0.976
Level of qualification			
Skilled worker	0.144	0.143	0.555
Unqualified employee	0.212	0.211	0.453
Qualified employee	0.494	0.495	0.738
Executive	0.150	0.151	0.418
Type of accompaniment[1] received from Pôle emploi			
Others	0.035	0.036	0.793
Reinforced	0.186	0.186	0.977
Guided	0.542	0.543	0.734
Follow-up	0.236	0.235	0.561
Diagnosed issues			
Professional project	0.208	0.207	0.811
Employment search	0.383	0.381	0.148
Other types	0.132	0.130	0.262
Direct return	0.161	0.162	0.902

Notes: Table 1 shows summary statistics for the sample of 252, 000 jobseekers. Column (1) and (2) present the mean in the control and the treatment group respectively. Column (3) presents p-values based on regressions that include batch fixed effects and heteroskedasticity-robust standard errors clustered by batch.

[1] (1) Reinforced: Intended for people who need intensive support.If they are assigned to this modality, jobseekers have more frequent contacts with caseworkers, and face-to-face meetings are preferred. The number of such jobseekers who can be accompanied by a caseworker is limited to 70 (2) Guided: is intended for jobseekers in an intermediate situation. The number of jobseekers who can be accompanied by a case worker is limited to 100-150. (3) Follow-up: Intended for jobseekers who are closest to the labour market and have the greatest autonomy. Dematerialised contact methods (telephone and e-mail) are preferred for communication with their caseworkers. The number of jobseekers who can be accompanied by a caseworker is 200 to 300.

3.2 Data

The PES also provided contact information as well as demographic and job search characteristics of jobseekers gathered in their administrative databases.

For the variables related to employment we use the national database ; *Déclaration Sociale Nominative*. Every month employers should transmit information about the situation of their employees at the time of the payroll. They should also relate events that occurred during the month and impacts on the payroll. This declaration is mandatory for private sector employers since January 2017 and January 2022 for the public sector.

To measure outcomes related to job search, we rely on databases provided by the PES. These databases contain information about actions taken by job seekers through the institution's mediation. It is important to note that we only observe job search activities that are done through the PES channel. We do not have access to job searches happening on other platforms. In addition to the administrative database, we also analyze the PES webpage logs. This database captures jobseekers' behavior and actions on the website, particularly on their profile page. This behavior is only observable when the jobseeker is logged into their account, which is mandatory to view their profile and to apply for job offers posted by recruiters on the institution's platform, but optional for job search and applications for job offers hosted by other platforms (which appear on the PES platform).

3.3 Experimental strategy

We estimate the effects of receiving an email promoting the profile on job search strategy, employment outcomes as well as jobseeker visibility by pooling the 7 batches and and running the following regression:

$$y_{it} = \alpha + \beta \times T_{it} + \mathbf{B}_t + u_{it}$$

where i and t index are respectively jobseekers and batch[5]. T equals to 1 if the job seeker was assigned to the treatment group, $\mathbf{B}$ corresponds to a vector of batch fixed effect and y an outcome of interest. We estimate heteroskedasticity-robust standard errors, clustered by batch. Our coefficient of interest is β which gives the effect on the outcome of interest of receiving an email about the online profile. We report intention-to-treat effects in this paper and discuss local average treatment effect in appendix **??**. To ensure that our results are not driven by statistical imbalances presented in **??**, we provide in the Appendix **??** regressions with controls added to the specification as a robustness check. All numerical variables are winsorized at the 99th percentile.

Our weekly samples are relatively small compared to the overall population of jobseekers in France (around 6 M). We will consider in this paper that there is no possible displacement effect.

4 Results

4.1 Profile filling and usage

Emails increase the share of participants who connected to the PES website and navigated to the profile page. The compliance rate is relatively low compared to other studies (ref). On average 15% of the control group against 17 % of the treatment group visited the profile page in a 60 days time-window (Table 2, column 1).

We also consider other indicators of profile usage, such as the probability of modifying, creating, or deleting a rubric on the profile, and the probability of publishing a profile on the platform. When recruiters query the profile bank, the default ranking of profiles is based on the date of the last modification. Although we do not have direct access to this ranking, we compute a proxy based on the probability of publishing a profile or modifying an existing one. We interpret this proxy as the probability of being pushed up in the ranking (Table 2, column 4). Treatment increased all measures of profile usage observed. 70 % of the people that visited the profile made a at least one modification of one category and half of them went up in the profile ranking.

[5]Which represents the week

Appendix **??** documents treatment effects on the probability to visit the profile page over time. Most of the treatment effects takes place within one week after sending the mail after which the treatment effect stays relatively constant.

Table 2: Treatment Effects on several proxies of profile usage, 60 days after email sending

	Visit	Any modification	Ranking up	Publication
Treatment	0.019***	0.013***	0.009***	0.002***
	(0.001)	(0.002)	(0.000)	(0.001)
Control mean	0.1476	0.1096	0.0919	0.0257
# Observations	252,000	252,000	252,000	252,000

*p<0.1; **p<0.05; ***p<0.01

This table shows results from equation (**??**) for different measures of profile usage observed in a 60-days window after sending the email: visiting at least once the skills profile, the observation of at least one modification of the skills profile, a proxy for having triggered a pushed up of the profile and the publication of the profile on the platform. All regressions include batches fixed effects. Standard errors are clustered at the batches level. The control mean is the average value for control jobseekers.

4.2 Treatment effect on employment

4.2.1 Access to employment

Our first employment outcome measure whether job seekers have found a job one and two months after the intervention. It corresponds to a dummy equals to 1 if we observe at least one contract in the month following the sending date. We also consider two additional outcome in order to characterize the stability of the contract. Jobseekers can be contracted under a permanent contract, a short term contract or really short-term contract. We measure the effect on permanent contract only as well as on the probability to get any contract with a duration of at least 1 month, we call this variable "Stable contract" [6] .

Our results presented in Table 3 and in Figure **??** indicate a positive influence of the email on the probability to find a stable or permanent job. However, except for some periods where we observe statistically significant differences between the control and the treatment group, the employment effects in the overall sample are mostly non significant.

Table 3: Treatment Effects on Access to employment

	At 30 days			At 60 days		
Type of contract	All	Stable	Permanent	All	Stable	Permanent
Treatment	0.000	0.000	0.001*	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Control mean	0.1562	0.0523	0.02346	0.2283	0.100	0.0428
Controls	No	No	No	No	No	No
# Observations	252,000	252,000	252,000	252,000	252,000	252,000

Note: *p<0.1; **p<0.05; ***p<0.01

[6] This is the definition of access to employment for the Public Employment service

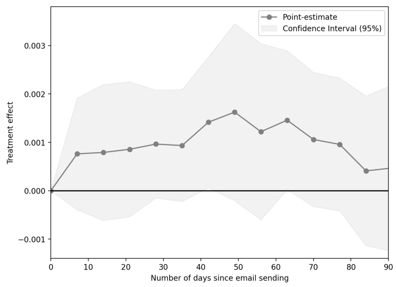

Figure 1: Access to permanent employment over time

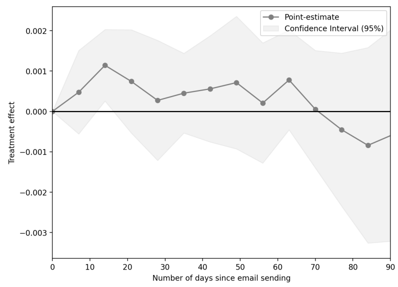

Figure 2: Access to stable employment over time

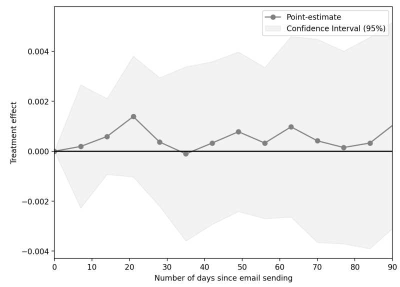

Figure 3: Access to employment over time

4.2.2 Other measures of match quality

A METTRE PLUS TARD ?

Table 4: Treatment Effects on Employment

	Number of days worked	Executive position	Cumulative Earnings
Treatment	0.121	0.0004	4.2453
	(0.182)	(0.002)	(4.363)
Control mean	28.93	0.051833	633
# Observations	252,000	252,000	252,000

Note:
*p<0.1; **p<0.05; ***p<0.01

5 Explaining impacts

5.1 Treatment effect on jobseeker visibility

Digital platforms could reduce information frictions by allowing firms to view more information about the productivity of jobseekers on profiles. Our intervention increased visibility of treated jobseekers compared to the control group. Moreover, recruiters were more likely to contact treated jobseekers.

Table 5: Treatment Effects on Job Seeker visibility

	Profile views		Contact propositions	
Type	Number	Probability	Number	Probability
Treatment	0.007	0.004***	0.003***	0.003***
	(0.001)	(0.015)	(0.001)	(0.001)
Control mean	1.609	0.144	0.0491	0.0640
Controls	No	No	No	No
# Observations	252,000	252,000	252,000	252,000

Note:
*p<0.1; **p<0.05; ***p<0.01

5.2 Treatment effect on job search behavior

5.2.1 Job search intensity

Besides having an impact on profile usage, our intervention could also have spillovers on job seeker general search behavior. As shown by Altmann et al. 2021, incentives can affect individuals' allocation of cognitive resources, induce a positive impact on the quality of decisions made on the domain targeted by the intervention but negative spillovers on other tasks. Filling one's profile requires high cognitive effort (document gathering and autonomous skill assessment). Therefore, we could expect a decrease in jobseekers' job search effort, at least in the very short run. Emails could also remind jobseekers of the PES's job-search related services and stimulate job search, leading to an overall ambiguous impact. Another spillover of our intervention could be the over-estimation of the likelihood of being contacted by a recruiter, leading jobseekers to reduce search effort. In a similar setting, Kelley et al. (2022) showed that jobseekers' beliefs about the arrival rate of jobs indeed mediated the effectiveness of matching interventions by a decrease of job search effort. These second spillovers could have a longer lasting effect than cognitive monopolization due to profile completion.

We focus on two measures of job search intensity ; visits to the PES job portal and autonomous applications. It is important to bear in mind that we exclusively observe jobseekers search behavior through the PES channel. Observed treatment effects could therefore be interpreted in two ways ; a modification of job search intensity or a modification of the channel through which jobseekers are looking for a job.

On average, our incentive triggered a negative impact on the number of visits on the job portal of the PES as well as on the number of applications made.

Table 6: Treatment Effects on Job Search

	Applications		Visits to ad webpages	
Type	Number	Probability	Number	Probability
group	-0.003***	-0.014***	-0.021**	0.000
	(0.001)	(0.004)	(0.011)	(0.001)
Control mean	0.311	0.0871	0.659774	0.1619
Controls	No	No	No	No
# Observations	252,000	252,000	252,000	252,000

Note:
*p<0.1; **p<0.05; ***p<0.01

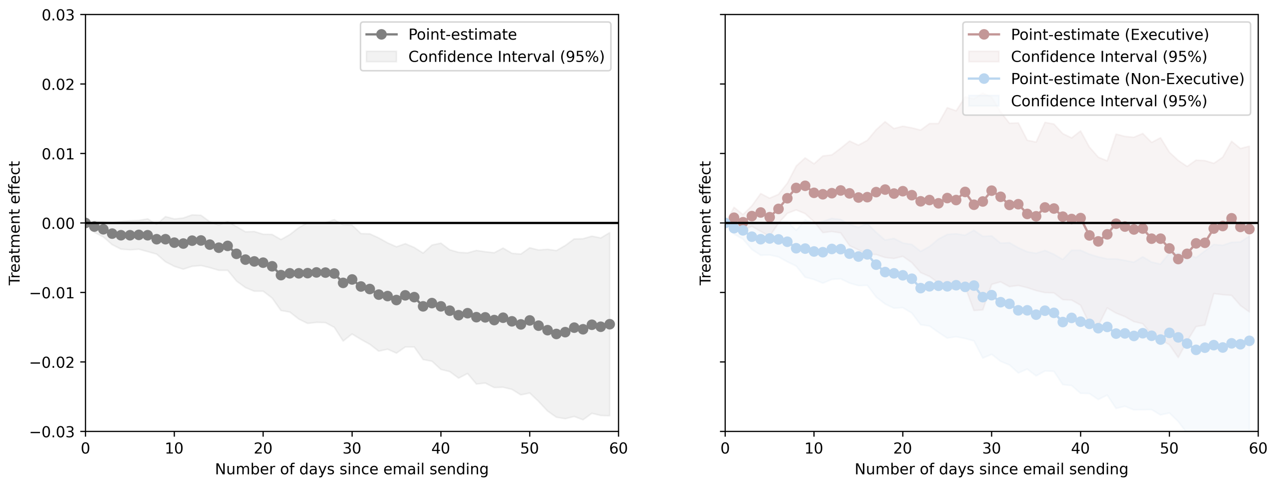

Figure 4: Number of applications

5.2.2 Treatment effect on other PES services usage

Our treatment could also have an impact on the use of other services proposed by the PES. We estimated the effect of emails on the probability of booking an appointment with the assigned caseworker and on participation in workshops. For both measures, we found no significant effect of the treatment (Table 7, column 1, 3).

Table 7: Treatment Effects on several proxies of PES services usage, 60 days after email sending

	Probability Meeting	# Meetings	Probability Workshop	# Workshops
Treatment	-0.002*	-0.001	-0.000	-0.001
	(0.001)	(0.003)	(0.001)	(0.003)
Control mean	0.2812	0.4647	0.122	0.395
# Observations	252,000	252,000	252,000	252,000

*p<0.1; **p<0.05; ***p<0.01

This table shows results from equation (**??**) for different measures of PES services usage observed in a 60-days window after sending the email. All regressions include batch fixed effects. Standard errors are clustered at the batch level. Number of meetings and workshops are winsorized at the 99th percentile. The control mean is the average value for control jobseekers.

5.3 Exploring heterogeneity dimensions

The impact of email might be heterogeneous among the population of job seekers, with some groups being more affected than others, despite a non-significant average effect. In order to explore heterogeneity dimension in a rigorous manner, we use the Generic Machine Learning approach developed by Chernozhukov et al. (2018). It prevents us from making any assumption on the relevance of any heterogeneity variables while avoiding multiple hypothesis testing.

Let's denote Y the outcome variable, $Y(0)$ and $Y(1)$ the potential outcomes in the treatment state 1 and the non-treatment state 0 and X a vector of covariates. The method leverages two key quantities ; the baseline conditional average $b(X) = \mathbb{E}[Y(0)|X]$ and the conditional average treatment effect (CATE) $s(X) = \mathbb{E}[Y(1) - Y(0)|X]$ both estimated using machine learning methods.

These estimates are used in order to test whether there exist heterogeneity in the treatment effect by performing the following regression :

$$Y_i = \alpha_0 + \alpha_1 \hat{b}(X_i) + \alpha_2 \hat{s}(X_i) + \beta_{ATE}(T_i - p(X_i)) + \beta_{HET}[T_i - p(X_i)][\hat{s}(X_i) - \mathbb{E}[\hat{s}(X_i)]] + \mathbf{B}_i + \epsilon_i$$

with $\hat{b}(X_i)$ and $\hat{s}(X_i)$ representing ML proxies at the individual level for the baseline conditional average and the CATE. If ML proxies of the CATE are good predictors for $s(X)$ then β_{HET} should equal 1. If ML proxies for the CATE are complete noise then β_{HET} should be null. If there is not heterogeneity in the treatment effect then $s(X) = s$ and $\beta_{HET} = 0$. Therefore, rejecting the hypothesis $\beta_{HET} = 0$ allows us to conclude that there is heterogeneity in the threatment effect and that our ML proxies are relevant. In the contrary, failing to reject the null hypothesis tells us or that our ML proxies is irrelevant, or that there is no heterogeneity in the data.

Our outcome variable, is the probability of access to employment 30 days after treatment. The covariates, include X baseline jobseeekers characteristics such as age, education, occupation and type of accompaniement given by the PES. The propensity score is constant. The procedure as well as the list of variables included are detailed in Appendix B.

	Random forest	
	β_{ATE}	β_{HET}
Estimate	0.0003	0.119
Conf. interval (95%)	[-0.003, 0.003]	[-0.0618 ,0.2999]
P-value (ajusted)	1.00	0.34

Note: Medians over X splits.

Table 8: BLP on access to employment at 60 days

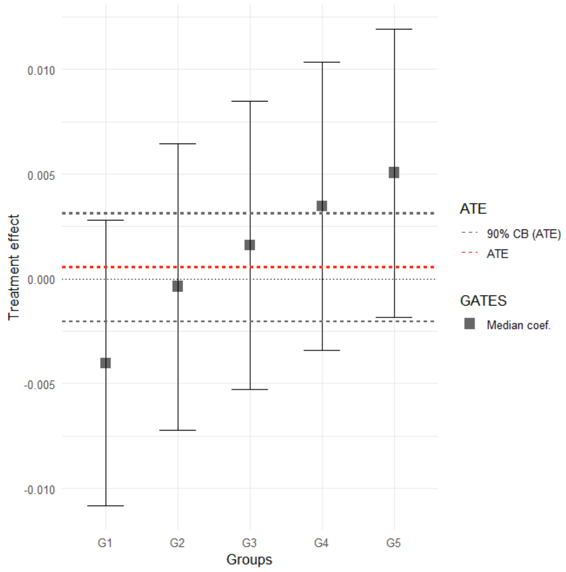

Figure 5: GATES on access to employment at 60 days

Table ?? reports estimates for β_{ATE} and β_{HET} from regression ??. The ATE estimates indicates that treatment did not increase employment at 30 days significantly. However, we find significant heterogeneity in the treatment effect as indicated by the statistically significant estimates for β_{HET}.

We turn to the estimation the GATES by quintiles. Figure 5 presents the estimated GATES coefficients.

Variable	Least affected	Most affected	Difference	pval
c_a_cv_c_1	0.22	0.21	-0.02	0.00
c_age_c	37.63	39.72	2.09	0.00
c_c_categoriede_1_c_1	0.63	0.64	0.00	0.00
c_c_categoriede_2_c_1	0.10	0.08	-0.02	0.00
c_c_categoriede_3_c_1	0.18	0.19	0.01	0.00
c_c_categoriede_4_c_1	0.04	0.04	0.00	0.00
c_c_categoriede_5_c_1	0.05	0.06	0.01	0.00
c_day_since_inscr_c	494.65	536.14	41.50	0.00
c_experience_rome_recherche_c	4.29	6.59	2.30	0.00
c_FREINS_c_1	0.13	0.13	-0.00	0.02
c_is_male_c_1	0.45	0.52	0.08	0.00
c_nb_entr_3mois_c	1.23	1.62	0.39	0.00
c_nb_visit_c	1.27	1.80	0.53	0.00
c_niveau_formation_AUTRE_c_1	0.18	0.12	-0.05	0.00
c_niveau_formation_BAC_c_1	0.24	0.24	0.00	0.00
c_niveau_formation_CAPBEP_c_1	0.26	0.31	0.05	0.00
c_niveau_formation_SUP_c_1	0.31	0.34	0.03	0.00
c_PROJETPRO_c_1	0.23	0.19	-0.04	0.00
c_qualification_rome_recherche_CADRE_c_1	0.11	0.20	0.08	0.00
c_qualification_rome_recherche_EMPLNQ_c_1	0.25	0.18	-0.06	0.00
c_qualification_rome_recherche_EMPLQ_c_1	0.47	0.49	0.02	0.00
c_qualification_rome_recherche_OS_c_1	0.18	0.12	-0.07	0.00
c_RECHEMPL_c_1	0.43	0.36	-0.07	0.00
c_remuneration_rome_recherche_c	1927.10	2122.10	192.27	0.00
c_RETOUR_c_1	0.18	0.17	-0.01	0.00
c_type_contrat_AUTRE_c_1	0.11	0.08	-0.03	0.00
c_type_contrat_CDD_c_1	0.29	0.19	-0.09	0.00
c_type_contrat_CDI_c_1	0.60	0.73	0.14	0.00
c_type_parcours_AUTRE_c_1	0.03	0.05	0.02	0.00
c_type_parcours_GUIDE_c_1	0.59	0.46	-0.13	0.00
c_type_parcours_RENFORCE_c_1	0.20	0.22	0.02	0.00
c_type_parcours_SUIVI_c_1	0.19	0.28	0.09	0.00

5.4 Heterogeneity in access to employment

Table 9: Treatment Effects on Access to employment

	At 30 days			At 60 days		
Type of contract	All	Stable	Permanent	All	Stable	Permanent
Treatment	-0.001	-0.000	0.000	-0.001	-0.001	0.000
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Treatment × Executive	0.007*	0.004	0.004***	0.009**	0.008*	0.006*
	(0.004)	(0.003)	(0.001)	(0.004)	(0.004)	(0.003)
Control mean	0.1551	0.0513	0.02281	0.2123	0.0893	0.0380
Controls	No	No	No	No	No	No
# Observations	252,000	252,000	252,000	252,000	252,000	252,000

Note: *p<0.1; **p<0.05; ***p<0.01

Table 10: Treatment Effects on Access to employment

	At 30 days			At 60 days		
Type of contract	All	Stable	Permanent	All	Stable	Permanent
Treatment	-0.000	-0.002**	-0.000	-0.001	-0.001	-0.000
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Treatment × Meeting	0.002	0.006***	0.003**	0.002	0.004***	0.004**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Control mean	0.1551	0.0513	0.02281	0.2123	0.0893	0.0380
Controls	No	No	No	No	No	No
# Observations	252,000	252,000	252,000	252,000	252,000	252,000

Note: *p<0.1; **p<0.05; ***p<0.01

6 Conclusion

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A Digital platform example

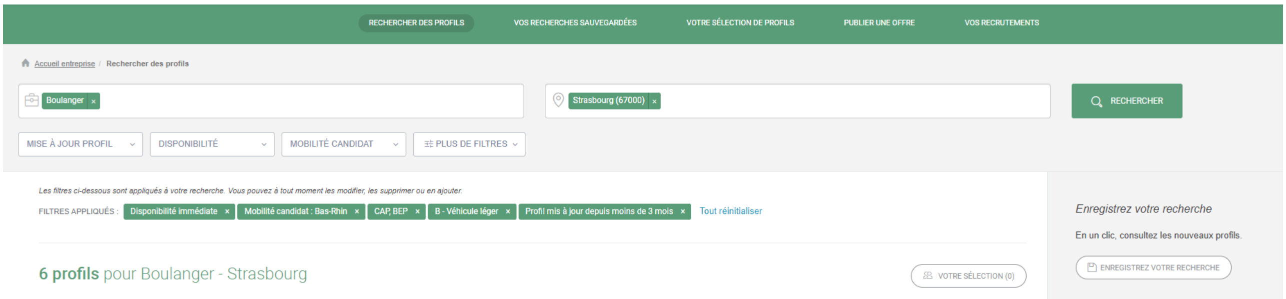

Figure 6: An example of search for a baker in Strasbourg

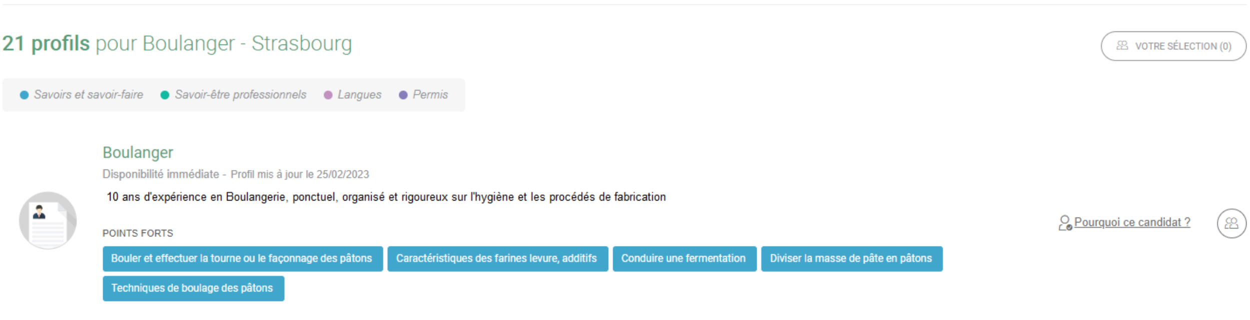

Figure 7: An example of SummaryCard for a baker

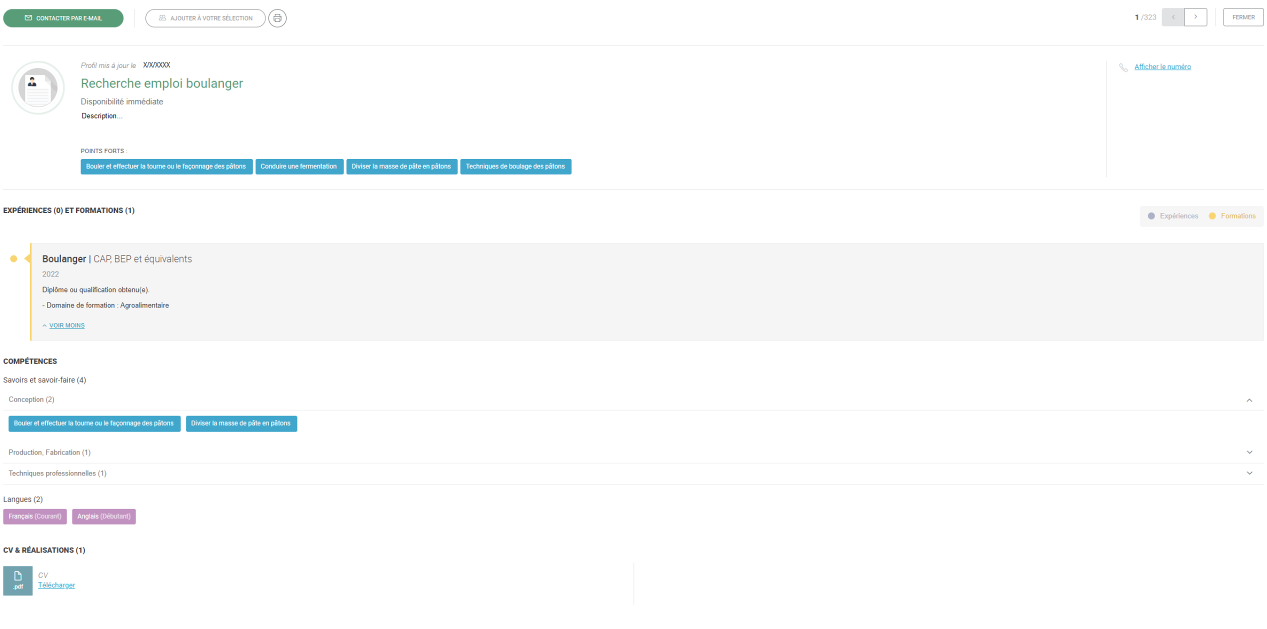

Figure 8: An example of a detailed profile for a baker

B Generic Machine Learning approach

B.1 Dynamics

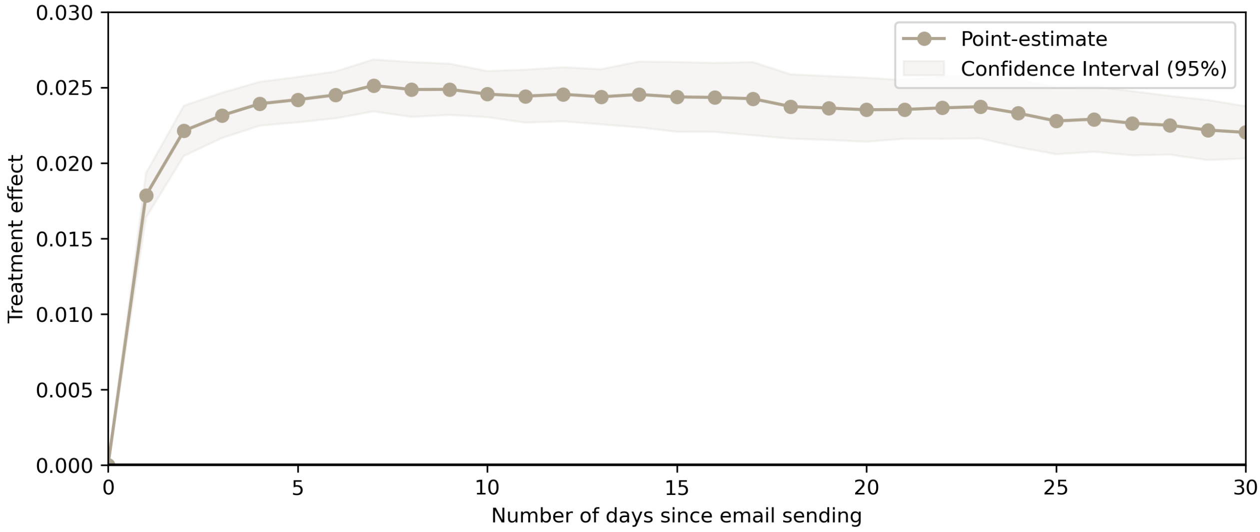

Figure 9: Treatment effect on the probability to visit the profile page over time

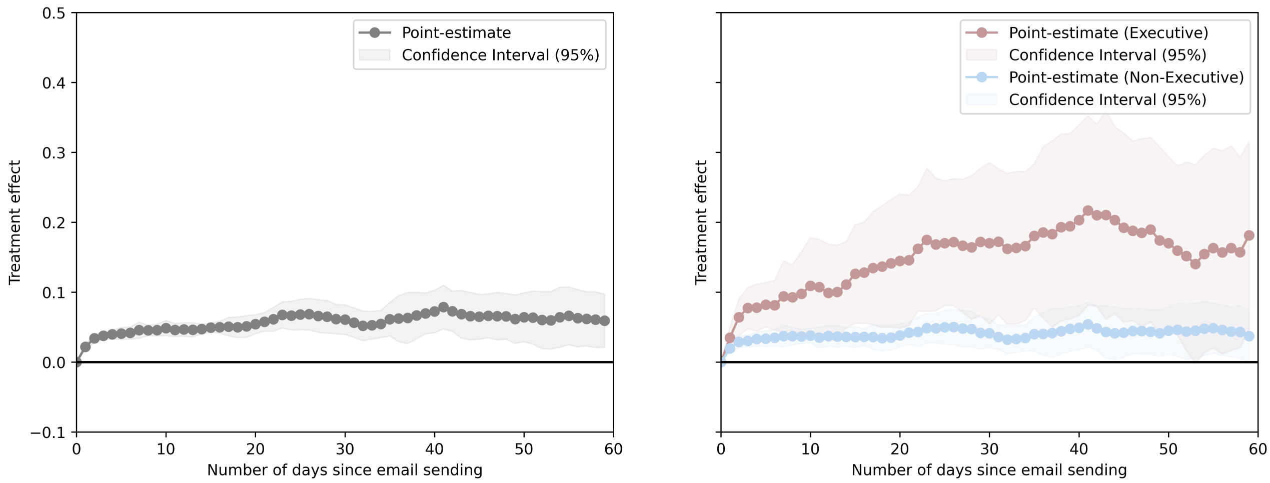

Figure 10: Treatment effect on the number of profile views by recruiters

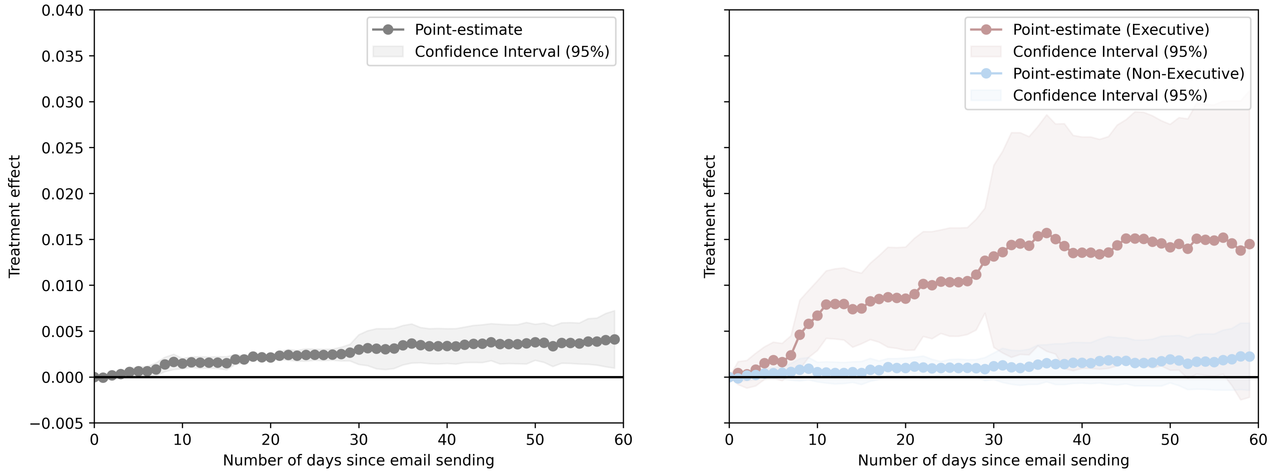

Figure 11: Treatment effect on the number of contact proposition from recruiters

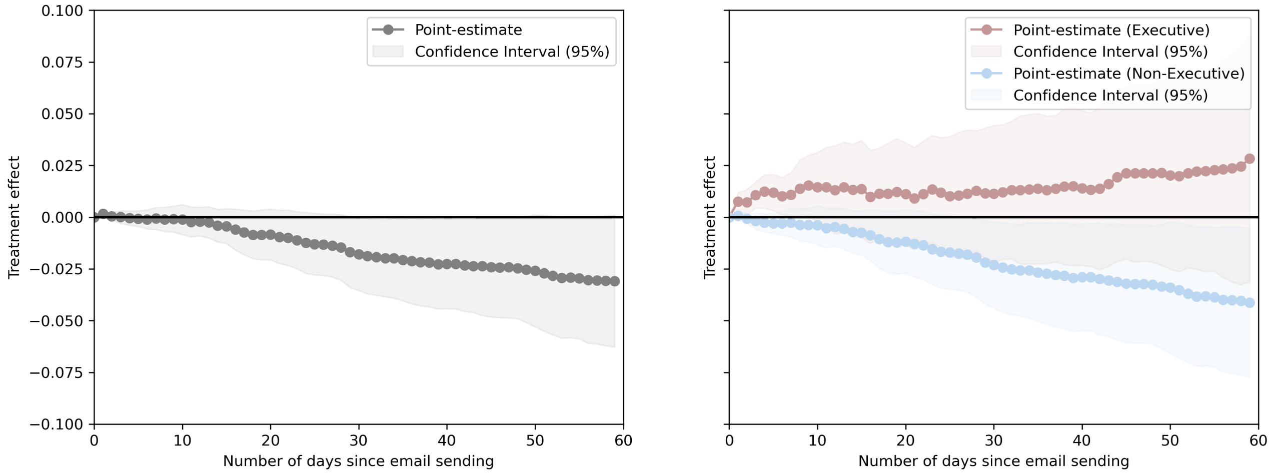

Figure 12: Number of visits to ad webpage