The Potential of Recommender Systems on the Labor Market: Experimenting at Scale

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NBER SI 2024, The Micro and Macro Perspectives of the Aggregate Labor Market — July 15th, 2024

Motivation

Frictions on the labor market = central in theories of unemployment [Pissarides (2000)]

$\rightarrow$ often summarized in reduced-form matching function [Petrongolo and Pissarides (2001)]

Micro-origins of matching frictions can be thought (in part) as a lack of information

$\rightarrow$ imperfect info. on hiring dynamics of specific firms?

$\rightarrow$ imperfect info. on opportunities in neighboring occupations? [Kircher (2020)]

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Public Employment Services (PES) admin data contains wealth of information on hiring and job search, at a detailed level (e.g., info. at CZ $\times$ occupation $\times$ firm level)

Can we use this information to reduce labor market frictions?

→ natural tool for doing so: internet-based platforms, with automated and tailored recommender systems trying to re-direct job search effort

Motivation

Recommender systems studied so far mostly for their ability to broaden job search (in particular, its occupational scope). Yet many more questions need to be answered to get closer to the design of efficient recommender systems:

1. can "algorithmic" predictions of firm-level hiring dynamics help improve targeting?
2. *when* should we recommend occupational broadening of job search?
3. how to take possible *congestion* effects into account?

Research goal = offering a way to study these questions experimentally to get a sense of the potential of recommender systems, and the challenges associated of their design.

Literature

The internet as “a labor market matchmaker”: idea from early 2000s [Autor (2001)]

- At first, little evidence of big progress in matchmaking efficiency [Kuhn and Skuterud (2004)]
- Yet in the early 2010s, growing observational evidence of the efficiency of internet job search [Kuhn (2014) and Kuhn and Mansour (2013)]

Renewal of the literature on the topic with growing ability to run (online) experiments to assess the efficiency of specific tools

- Online or offline screening tools for firms [Algan, Crépon, and Glover (2023) and Horton (2017)]
- Recommender systems for job seekers [Altmann et al. (2023), Belot, Kircher, and Muller (2019), Bied et al. (2023), and Hensvik, Le Barbanchon, and Rathelot (2023)] $\longrightarrow$ our paper

Preview of the paper

- Design of an experiment that takes into account economic interactions (congestion) and mechanisms (firm heterogeneity, occupational switching costs)
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  1. large occ. switching costs, potentially offset if re-directing indiv. from slack to tight mkts
  2. potentially large gains associated to algo. predictions of firm-level hiring dynamics
- Some evidence of potential congestion effects $\Rightarrow$ importance to take these into account in the design of recommender systems

Experimental design

Recommender system, online platform and sample

Design of recommender system w/ personalized e-mails, redirecting to existing platform

- Recommender system build following insights from a heuristic economic model
  $\rightarrow$ generating useful identifying variation, taking into account constraints from economic environment
- Recommendations sent to job seekers via the PES system
- E-mail re-directing towards an existing online platform “La Bonne Boîte” (The Right Firm)
  Specific feature = prediction of firm$\times$occupation level hiring (based on past hires in admin data), *irrespective of vacancy posting behavior* $\rightarrow$ predictions used in the design of our recommender system

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Evaluating the recommender system at scale, on a quarter of French labor market

- 94 out of 406 French commuting zones (CZ) involved
- 800,297 active job seekers in these CZ on Nov. 1^{st}, 2019 (launch date)
- 98,366 firms in these CZ listed on our platform on Nov. 1^{st}, 2019 (launch date)

Trouvez ici les entreprises qui recrutent régulièrement, et contactez-les !*

Métier recherché : (boucher, cariste, secrétaire, ...)

Autour de : (Paris, Bd Voltaire, 33000...)

Vous recherchez un contrat en alternance ? Les entreprises susceptibles de vous recruter sont sur La Bonne Alternance.

*Grâce à un algorithme exclusif de Pôle emploi détectant les entreprises qui vont probablement embaucher ces 6 prochains mois.

UNION EUROPÉENNE
l'Europe s'engage en France
Ce dispositif est cofinancé par le Fonds Social Européen dans le cadre du Programme opérationnel national "emploi et inclusion" 2014-2020

Enseignement supérieur

Paris 75001

Masquer la carte

Trier

Tri optimisé ?

Distance

Affinez votre recherche

Secteur d'activité

Tous les secteurs

Taille de l'entreprise

Toutes tailles

Moins de 50 salariés

Plus de 50 salariés

Distance

5 km

10 km

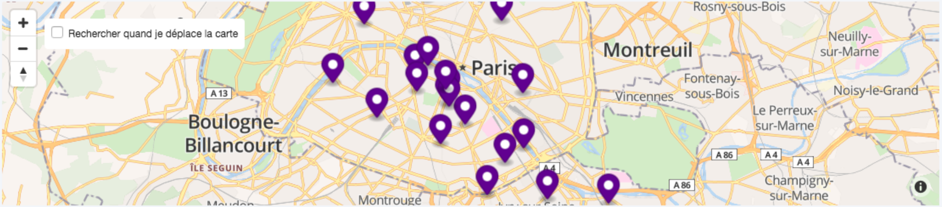
30 km

50 km

100 km

+ de 100 km

181 entreprises sont susceptibles de recruter en Enseignement supérieur autour de Paris



UNIVERSITEPARIS1PANTHEON-SORBONNE - PARIS-05

Enseignement supérieur

500 à 999 salariés

km 2.2 km de votre lieu de recherche

Potentiel d'embauche

★★★★☆ 4.4

Plus d'infos +

Enregistrer dans MEMO

Postuler

UNIVERSITE PARIS DIDEROT - PARIS 7 - PARIS-13

Enseignement supérieur

250 à 499 salariés

Potenti

Donner votre avis

Email content

Dear Mr./Mrs. [X],

You are currently registered with the public employment service and are looking for a job as a [X's occupation of search].

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 the Public Employment Service, has selected for you several 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,

Several levels of randomness

At a high-level, the experiment can be summarized as randomizing 3 main elements:

- At the job seeker level

$$Z_i \in \{0, 1\} = \text{Control vs Treated}$$

- At the job seeker $\times$ firm level

$$R_i^j \in \{0, 1\} = \text{Not recommended vs Recommended}$$

- Firms are recommended **more or less frequently** (“few” and “many” treatment arms)
  $\rightarrow$ useful to assess the existence of congestion effects

Summing up

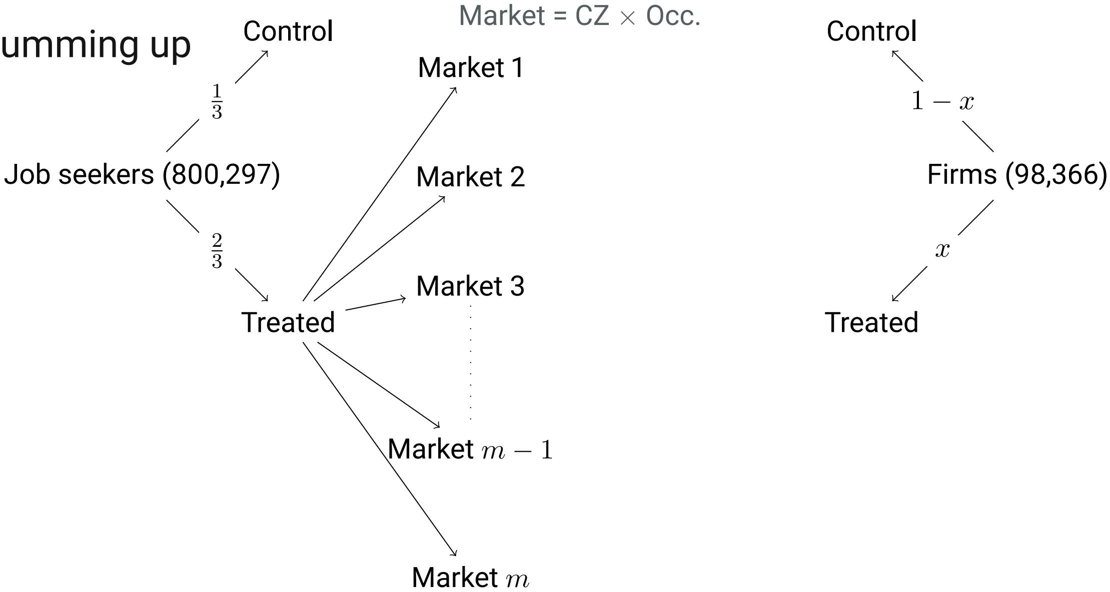
Job seekers (800,297)

Firms (98,366)

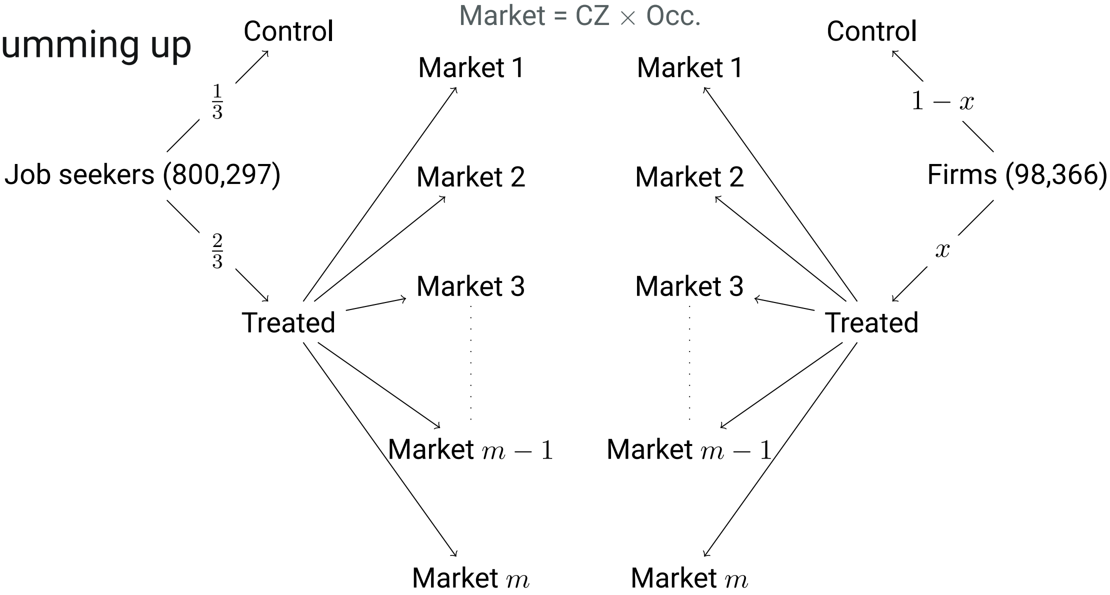
Summing up

$$\begin{tikzcd}[column sep=small] & \text{Control} \\ \text{Job seekers (800,297)} \arrow[ur, "\frac{1}{3}"] \arrow[dr, "\frac{2}{3}"'] & \\ & \text{Treated} \end{tikzcd} \qquad \begin{tikzcd}[column sep=small] \text{Control} & \\ & \text{Firms (98,366)} \arrow[ul, "1-x"'] \arrow[dl, "x"] \\ \text{Treated} & \end{tikzcd}$$

Summing up


Market = CZ $\times$ Occ.
Control
$\frac{1}{3}$
Job seekers (800,297)
$\frac{2}{3}$
Treated
Market 1
Market 2
Market 3
Market $m-1$
Market m
Control
$1-x$
Firms (98,366)
x
Treated

Summing up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Market 1
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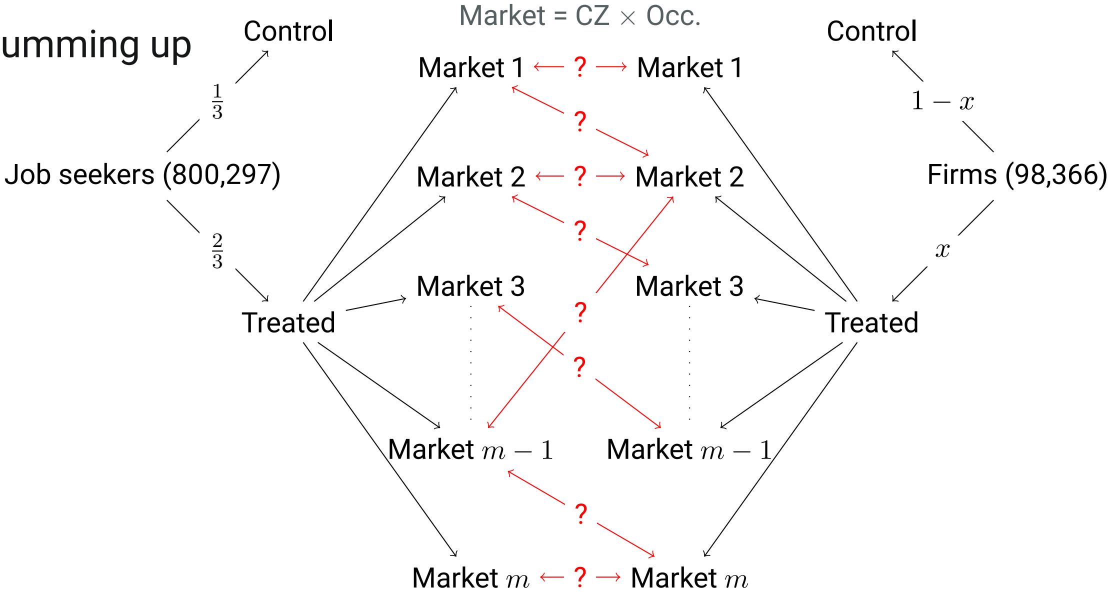
Summing up



Pairwise recommendations

Matching job seekers and firms

We need to make pairwise recommendations that

1. ... induces randomness $\rightarrow$ to identify the effect of recommendations
2. ... while generating sensible recommendations (that may have an impact & are worth studying)
3. ... and limiting congestion frictions

Challenging task, requiring to strike some balance between:

- completely random draw $\rightarrow$ random but ~~crazy~~ recommendations
- recommending firm(s) with highest Pr(Hire) $\rightarrow$ sensible rec. but ~~congestion~~

Design

Best shot at taking into account congestion & important dimensions of the hiring process (occupational switching costs, firm-level heterogeneity in hiring prospects etc.) in a principled way:

- Start with a heuristic model of the labor market with:
  1. many markets (= CZ$\times$occupation)
  2. occupation switching costs
  3. firm level congestion ("frictions") in hiring technologies
- Absent frictions: send workers in own occupation, to firm w/ highest predicted hirings
- 2^{nd} best: trade-off occupational distance, firm-level hiring prospects & congestion...

  ... by solving for an "optimal" vector of propensity scores $\pi_i^j = P(R_i^j = 1)$

Modeling of the hiring process (in a nutshell)

Brief summary of the heuristic model of hiring we use:

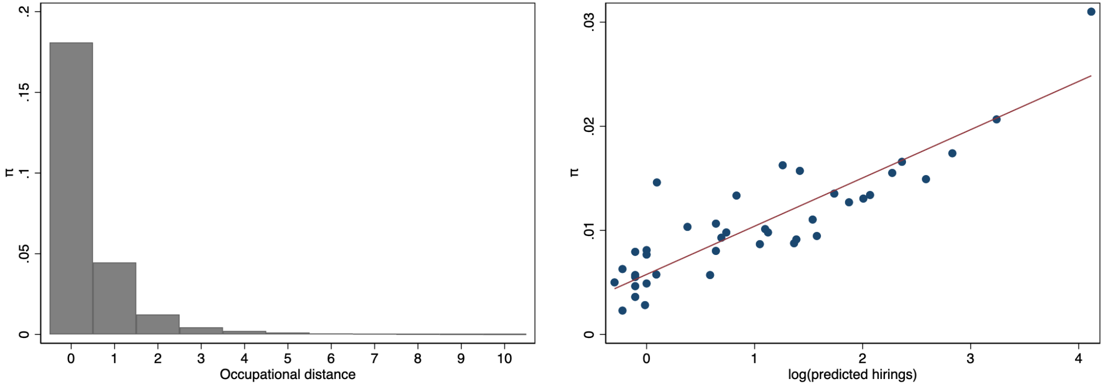
1. We send a recommendation: $R_i^j = 1$
2. Workers apply (or not): $A_i^j \rightarrow P(A_i^j)$ decreasing in occupational distance btw. i and j
3. Firms receive applications
$$A^j = \sum_j A_i^j$$
4. Firms screen applications with probability q, function of the ratio between nb. of applicants A^j and (predicted) hirings V^j
$$q\left(\frac{A^j}{V^j}\right) \in (0,1) \qquad \text{with } q' < 0 \quad \text{(hence congestion)}$$
5. Firms hire screened applications H_i^j (or not) $\rightarrow$ decreasing in occ. distance btw. i and j

Dyad-level recommendation proba. π_i^j computed to max. expected hiring: $\mathbb{E}_\pi[\sum_i \sum_j H_i^j]$

$\Rightarrow$ negatively correlated with occ. distance [left panel]

$\Rightarrow$ positively correlated with firm level predicted hirings [right panel]

[Bonus: very high positive correlation with firms' AKM wage fixed effects.]



Now we're equipped to experimentally test these mechanisms!

Now we made it here, with an experimental design that takes into account that

1. Proba. that firm j hires indiv. i (conditional on application) may decrease w/ occ. distance
2. Firms w/ better (predicted) hiring prospects have higher proba. to hire i (cond. on app.)
3. Proba. that firm j hires applicant i may decrease w/ tot. nb. of applicants (congestion)

The empirical relevance (or irrelevance?) of each of these mechanisms will be documented, using the identifying variation generated by our experiment.

Results

Job seekers' characteristics

	(1) Control		(2) Treated		(3) Difference	
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	

Take-up

	Mean	Sd.	N
	A. Tracking data		
(i) Received email	0.96	0.19	533,557
(ii) Opened email	0.64	0.48	533,557
(iii) Click	0.25	0.43	533,557
	B. Job seeker survey		
(iv) Application rate	0.073	0.260	8,061

Additional info. from survey:

- Nb. of applications per job seeker $\approx$ 40
  (over the 4 months of experiment)
- No significant increase in total nb. of applications among treated job seekers
- Treated job seekers increase use of LBB
  (share of users: from 0.2 to 0.25)

Reduced form at job seeker level

	(1) All	(2) Long term	(3) Short term
Treated (Z_i)	0.0008	-0.0007	0.0014
	(0.0009)	(0.0005)	(0.0008)
	[0.42]	[0.16]	[0.09]
Baseline	0.19	0.04	0.15
Observations	800,297	800,297	800,297

Notes. Standard errors clustered at the labor market (CZ $\times$ Occupation) level. P-values in brackets.

Small employment effect, concentrated on short term contracts.

Limited magnitude may not be surprising given nature of intervention (3 e-mails).

Our goal is rather to learn about the *potential* of such interventions (and how to best design them).

But did *anything* happen through the use of the LBB platform?

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Reduced form by type of firm for short term contracts

	(1) All	(2) Not LBB	(3) LBB
Treated (Z_i)	0.00142	0.00030	0.00112
	(0.0008)	(0.0007)	(0.0005)
	[0.09]	[0.67]	[0.04]
Baseline	0.154	0.097	0.057
Observations	800,297	800,297	800,297

Notes. Standard errors clustered at the labor market (CZ $\times$ Occupation) level.

Did *anything* happen through the LBB platform?

Fortunately, yes.

... Suggesting that we may have been successful at re-directing search effort.

The only way to study that in more detail is to look at the specific effect of recommending job seeker i to firm j.

Dyad-level analyses

Did we redirected search effort through our recommendations (to job seeker i, towards firm j) ?

We should study two average treatment effect in order to answer this question.

The first and most natural one is the targeting effect

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

$\rightarrow$ comparing outcomes of recommended vs non-recommended pairs of *treated* indiv.

Yet maybe (i) treated job seekers *reallocate* their search effort from non-recommended to recommended firms, or (ii) they are more active *in general* on LBB.

These reactions would be captured by another "residual" effect

$$\mathrm{RES} \equiv \mathbb{E}\left[Y_i^j(Z_i = 1, R_i^j = 0) - Y_i^j(Z_i = 0, R_i^j = 0) \mid R_i^j = 1\right]$$

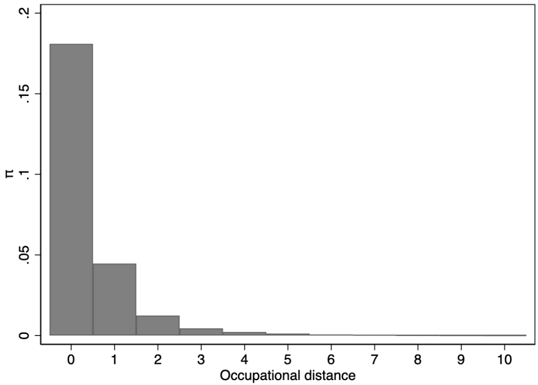
$\rightarrow$ comparing outcomes of *non-recommended* pairs treated vs. control indiv.

Targeting effect heterogeneity by recommendation type

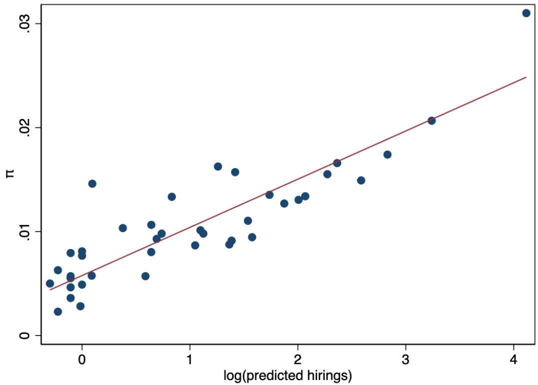
	TARG (1)	RES (2)	TARG (3)	RES (4)
	ATT		ATE	
(a) R_i^j avr. effect ($\times 100$)	0.00734	0.00403	0.00457	-0.00001
	(0.0033)	(0.00350)	(0.00212)	(0.00031)
	[0.03]	[0.25]	[0.03]	[0.96]
(b) Baseline ($\times 100$)	0.04176	0.03773	0.01205	0.01206
N	49,068,302	71,341,446	49,068,302	71,341,446

ATT $\neq$ ATE suggests treatment effect heterogeneity $\rightarrow$ our recommender system has encouraged applications where they were more efficient (higher chances of success)?

Figure: CORRELATIONS OF RECOMMENDATION PROBABILITIES WITH OCCUPATIONAL DISTANCE AND WITH PREDICTED HIRINGS



((a)) Occupational distance



((b)) Predicted hirings

Decomposing our targeting effect

We can identify avr. application efficiency μ (using data on hires + survey data on applications) (among all vs. recommended dyads, and by categories — cf. heterogeneity analysis) .

$$\mu \equiv E(Y_i^j(A_i^j = 1) - \underbrace{Y_i^j(A_i^j = 0)}_{=0}) \quad (\text{conditioning or not on } R_i^j = 1 \text{ etc.})$$

Under further assumptions (akin to homogeneity of μ btw. compliers of our experiment and always-applicants), we can decompose our targeting effect (ATT or ATE) as

$$\text{TARG} = \mu \cdot \quad \underbrace{(\rho - \rho_0)}_{\text{Diff. take-up rate}}$$

where ρ is the application rate of i to j when $R_i^j = 1$, and ρ_0 the same when $R_i^j = 0$.

Targeting and residual effects — decomposition

	TARG	RES	TARG	RES
	(1)	(2)	(3)	(4)
	ATT		ATE	
(a) R_i^j avr. effect ($\times 100$)	0.00637	0.00413	0.00457	-0.00001
	(0.00334)	(0.00355)	(0.00212)	(0.00031)
	[0.06]	[0.25]	[0.03]	[0.96]
(b) Baseline ($\times 100$)	0.0424	0.0382	0.01205	0.01206
μ: application efficiency	0.00673		0.00254	
$= \frac{1}{100} \cdot \frac{\text{(a)} + \text{(b)}}{\rho}$	(0.0008)		(0.0005)	
$\rho - \rho_0 = \frac{\text{(a)}}{\mu}$	0.0095		0.0179	
ρ: application rate	0.0725		0.0654	

How should we design efficient recommender systems?

The previous results suggest substantial heterogeneity in μ along dimensions identified as relevant by our design.

Order of magnitudes for application efficiency μ (= proba. of hire conditional on applying) :

- Average job finding rate after 4 months $= 0.19$
- Average number of applications sent $= 40$

$\Rightarrow$ Average application efficiency $= \frac{0.19}{40} = 0.00475 \in [\mu^{\text{ATE}} = 0.00254,\ \mu^{\text{ATT}} = 0.00673]$

With average μ, 1 application out of 210 is successful.
With efficiency μ^{ATT}, 1 application out of 150 is successful: meaningful difference!

Can we learn from our experiment to improve the design of future recommender systems?

Heterogeneity by recommendation type

	$d = 0$	$d > 0$	Pred. hirings below med.	Pred. hirings above med.	Mkt. tightness below med.	Mkt. tightness above med.
	(1)	(2)	(3)	(4)	(5)	(6)
(a) ATT ($\times 100$)	0.00706	0.00444	0.00282	0.00907	0.00591	0.00732
	(0.00462)	(0.00245)	(0.00198)	(0.00545)	(0.00284)	(0.00802)
	[0.13]	[0.09]	[0.16]	[0.10]	[0.04]	[0.36]
(b) Baseline ($\times 100$)	0.0515	0.0172	0.0149	0.0633	0.0357	0.0564
μ: application efficiency	0.00727	0.00481	0.00276	0.00920	0.00573	0.00883
$= \frac{1}{100} \cdot \frac{\text{(a)} + \text{(b)}}{\rho}$	(0.00094)	(0.00127)	(0.00056)	(0.00134)	(0.00081)	(0.00178)
[p-val. diff.]		[0.12]		[0.00]		[0.11]
$\rho - \rho_0 = \frac{1}{100} \cdot \frac{\text{(a)}}{\mu}$	0.0097	0.0092	0.0102	0.0098	0.0103	0.0082
ρ: application rate	0.0805	0.0449	0.0642	0.0786	0.0726	0.0721

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Congestion effects?

	Few rec.	Many rec.
	(1)	(2)
μ: application efficiency	0.00738	0.00641
	(0.00094)	(0.00077)
[p-val. diff.]		[0.09]

Notes. Standard errors clustered at the labor market (CZ $\times$ Occupation) level. Average nb. of recommendations made to firms in treatment arm "Few" is 42, while it goes up to 84 for firms in treatment arm "Many".

Comparison of firms with few (42) vs. many (84) recommendations allows to identify possible congestion effects.

We do observe a marginally significant *decrease* in application efficiency btw. the two set of firms.

... Suggesting the importance of taking into account congestion in the design of recommender systems (keep in mind ours was designed to limit congestion).

▸ Supercontrol comparison

Summing up

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- Some evidence of potential congestion effects (despite efforts to limit them) $\Rightarrow$ importance to take these into account in the design of recommender systems

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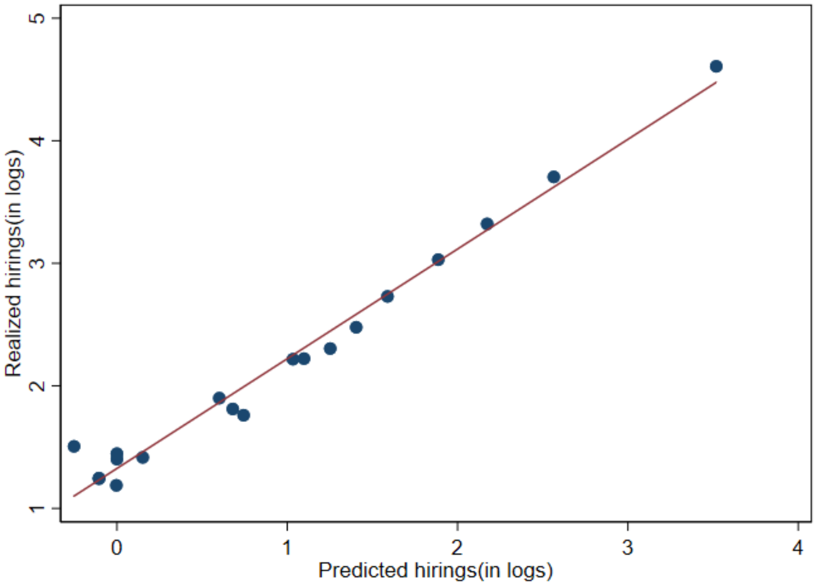
Appendix

Correlation between predicted and realized hires



Synthetic DID results

	Treated vs. SC	Control vs. SC
	(1)	(2)
Treated Market	0.0031	0.0017
	(0.0016)	(0.0017)

Notes. Standard errors computed using placebo simulations.

Initial (unlucky) imbalance in employment dynamics btw. treated and super-control mkts. $\rightarrow$ Corrected using admin data on past employment dynamics.

Significant total effect when comparing treated indiv. and super-controls. [Similar order of magnitude as direct effect found.]

No significant displacement effect detected... yet clearly underpowered test.

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