### Directing job search: a large scale experiment.

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# TEMPORARY SLIDE DECK - UPDATES WILL BE MADE

#### Introduction

La Bonne Boîte

Experimental design and data

Reduced-form results

Structural approach to occupational frictions

Conclusion and road ahead

1. Can we improve the matching of job seekers and firms by encouraging job seekers to send spontaneous job applications to specific firms?

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- 2. Does the implied reduction in hiring costs lead to increased labor demand?

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- ► Large scale: 94 commuting zones (CZs), 100,000 establishments, 1.2m job seekers, treated in Nov-Dec 2019, and followed in administrative data until mid March 2020 (lockdown)
  - (+ short survey on sample of job seekers, mid Jan.)

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- ▶ Robust, precise, reduced-form evidence on marginal impact of increased platform use.

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- Displacement effects
  - Super controls (untreated commuting zones) not useful (lack of statistical power, given small effect sizes)
    - ▶ second experiment (Fall 2020) might provide evidence on displacement effects across occupations (does redirecting job seeker's search from (crowded) occupation A to (less crowded) occupation B reduce employment in occupation A?)

# What this paper starts doing

- Structural interpretation
  - Simple model of local labor market equilibrium has already been used to ensure consistency between randomization on two sides of the market
  - Random components added to the model provide credible variations to identify model's key mechanism, with survey data to analyze intermediary outcomes.

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    - ► early elements today

#### Literature

#### Job seekers

- Overall effect of internet job search: Kuhn and Skuterud (2004), Stevenson (2009), Thomsen and Wittich (2010), Kuhn and Mansour (2013)...
- Providing specific recommendations based on occupational distance: Belot, Kircher and Muller (2018).
- Overall activation effect: Altmann et al (2018)
- Displacement effect: Crépon et al (2013)

### **Firms**

- ▶ Effect of broadband expansion: Bhuller et al (2019)
- ► Through pre-screening of applications: Algan et al (2018)
- ▶ Algorithmic recommendations of job seekers: Horton (2017).

#### Mismatch

 Occupational mismatch more costly than spatial mismatch (Marinescu & Rathelot 2018)

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### La Bonne Boîte

- "La Bonne Boîte" (LBB) is an online search engine which predicts which establishments are likely to hire (based on past hirings).
  - Predictions independent from whether the firm posted vacancies.
- ▶ LBB helps job seekers locate local firms that are likely to hire in their particular occupation.

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  - Predictions independent from whether the firm posted vacancies.
- ▶ LBB helps job seekers locate local firms that are likely to hire in their particular occupation.
- Goals:
  - Encourage active labor search on the hidden job-to-job labor market
  - 2. Complement Pôle emploi job placement services.

Predictions





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



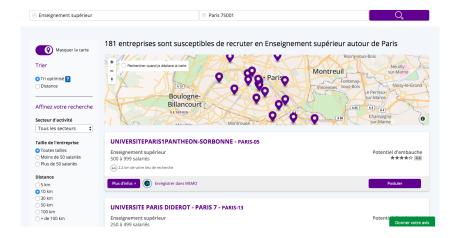
\*Grâce à un algorithme exclusif de Pôle emploi détectant les entreprises qui vont probablement embaucher ces 6 prochains mois.

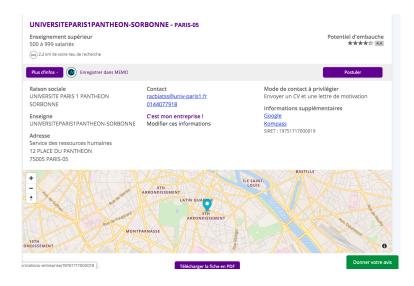
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#### Introduction

#### La Bonne Boîte

### Experimental design and data

Experimental treatments
Commuting zones and strata
Matching job seekers and firms
Realized treatment
Balance

Reduced-form results

Structural approach to occupational frictions

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### Experimental treatments

LBB active since 2015, so treatment = randomly induced variations in exposure to service

- e-mails to randomly selected job seekers (=encouragement design)
  - encouragement to use LBB to make spontaneous applications
  - hyperlinks to specific establishments

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- e-mails to randomly selected job seekers (=encouragement design)
  - encouragement to use LBB to make spontaneous applications
  - hyperlinks to specific establishments
- 2. random variation in which establishments (among "bonnes boîtes") are recommended to job seekers
  - by putting them on top of the list on the search engine
  - by recommending them in the e-mails to job seekers.

### Email treatment

#### Each mail contains

- 1. Each job seeker's self-declared search occupation
- General information on spontaneous applications and LBB service
- 3. One or two direct links to the LBB page of selected firms
- 4. General information on how to apply to the suggested firms and link to LBB's search engine.

#### Table: Email 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]:

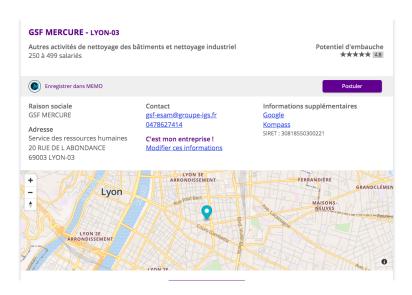
- [Link to recommended establishment 1]

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,



# Experiment's scope

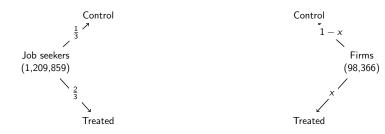
Pôle emploi divides France into 404 commuting zones. For the purpose of our experiment we randomly select 94 of them. These 94 commuting zones encompass:

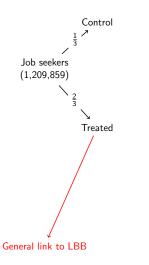
- ▶ 1,209,859 job seekers
- ▶ 98,366 hiring establishments

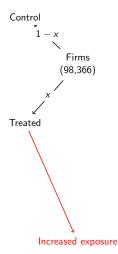
Stat CZ

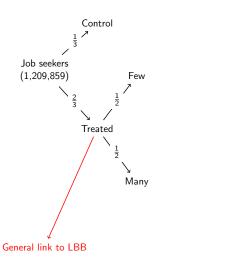
Job seekers (1,209,859)

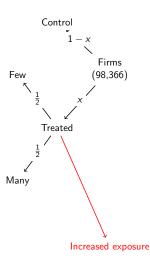
Firms (98,366)

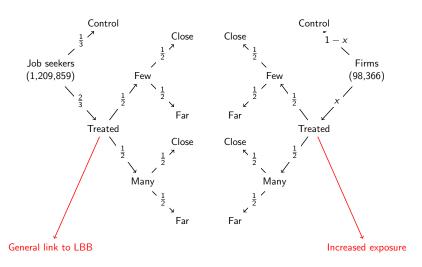


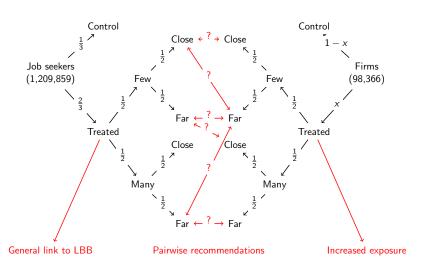












#### Strata

### Commuting zones

- Quintile of size (number of job seekers)
- Quintile of tightness (predicted hirings/number of job seekers)

#### Job seekers

- Commuting zone
- Occupation (ROME)
- Above/below median of predicted exit rate out of unemployment

#### **Firms**

- Commuting zone
- Sector (5-digit APE code)
- Above/below median of total predicted hirings



# Matching job seekers and firms

On both sides of the market we now know:

- who is going to be treated,
- how much they should be treated,
- how far in the occupational space they should be sent.

#### Question:

What specific job seeker/firm pairwise recommendations should we make to realize the desired treatment of each agent?

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We make our recommendations based on an explicit model of the labor market in which we incorporate random variations in the number and proximity of desirable recommendations (more on this in 33').

#### Realized treatment

Job-seekers Establishments

A - Number of distinct recommendations

	Close	Far	Close	Far
Few	3.17	3.21	18.3	28.6
Many	5.51	5.73	39.9	63.3

B - Average distance of recommendations

	Close	Far	Close	Far
Few	0.55	1.26	0.09	0.68
Many	0.56	1.25	0.10	0.71

Note: Panel (A) displays job seekers' mean number of distinct recommendations and establishments' mean number of distinct recommendations per predicted hiring within each treatment arm. Panel (B) displays the mean average distance of job seekers' and establishments' recommendations within each treatment arm.

## Job seekers' balance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	C		Т		T-C		F-test
Male	0.474	(0.499)	0.475	(0.499)	0.000	(0.001)	0.69
Age	37.684	(11.972)	37.720	(11.962)	0.036	(0.023)	0.95
Diploma	0.615	(0.487)	0.615	(0.487)	-0.000	(0.001)	0.63
Experience (y)	6.630	(7.915)	6.633	(7.915)	0.003	(0.015)	0.25
Unemployment spell (m)	21.359	(25.926)	21.399	(25.917)	0.041	(0.050)	1.02
Predicted exit rate	0.213	(0.071)	0.213	(0.071)	0.000	(0.000)	0.69
Predicted tightness	0.397	(0.657)	0.397	(0.658)	0.000	(0.001	1.04
Present at treatment	0.661	(0.473)	0.662	(0.473)	0.000	(0.001)	0.84
Observations	403,422		806,437		1,209,859		1,209,859

Table: Balance table for job seekers' observables.

## Firms' balance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	C		Т		T-C		F-test
Predicted hirings	4.909	(0.065)	4.856	(0.073)	-0.053	(0.098)	0.772
Contact email available on LBB	0.476	(0.002)	0.471	(0.002)	-0.004	(0.003)	0.630
Predicted tightness	0.538	(0.002)	0.538	(0.002)	-0.001	(0.004)	0.999
Initial hirings (all)	36.104	(2.129)	32.693	(2.068)	-3.410	(2.969)	0.342
Initial hirings (indefinite)	3.862	(0.057)	3.770	(0.092)	-0.092	(0.108)	0.759
Initial hirings (definite)	32.242	(2.125)	28.923	(2.062)	-3.319	(2.961)	0.331
Posted offer at PES	0.492	(0.002)	0.494	(0.002)	0.002	(0.003)	0.177
Observations	59556		38810		98366		98366

Table: Balance table for firms. Each firm is re-weighted by the inverse probability of its treatment status.

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#### Reduced-form results

Pairwise recommendations (dyads)

Job seekers

Job seekers

Firms

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- ▶ Look at the space of potential recommendations:
  - $R_{i,j} = 1$  the fact that we recommended firm j to job seeker i
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- ▶ What is the effect of recommending firm j to job seeker i rather than to job seeker i'?
- ▶ Restrict to job seeker/firm pairs within the same occupation so that in our design:  $P(R_{i,j} = 1) = P(R_{i',j} = 1)$
- Careful: no SUTVA! Results should be interpreted conditional on the range of congestion/reallocation effects created by the experiment.

## Directing job search?

	$H_{i,j}$	$H_{i,j}$	$H_{i,j}$
$R_{i,j}$	0.0170	0.0123	0.0194
	(0.00241)	(0.00294)	(0.00308)
Constant	0.0108	0.0106	0.0110
	(0.000108)	(0.000163)	(0.000122)
Sample	All	Males	Females
N	29,330,163	10,035,723	19,293,546

Standard errors in parentheses.

Note: Effect of recommendations on hirings at the dyadic level and including firm fixed effects. Restricted to job seekers/firms pairs in the same occupation. Standard errors clustered at the CZ level. Reported results are in percentage points.

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- ▶ next step = ITT effects on job seekers (resp.firms)

# Job seekers

Take up

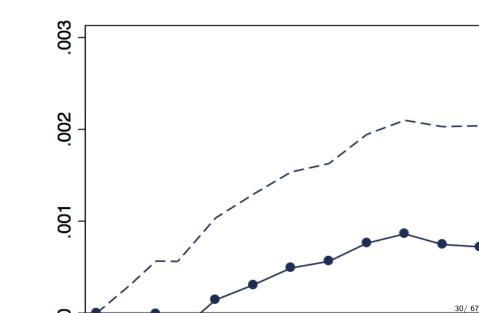
#### Job seekers

#### Take up

	mean	sd	count
Received email	0.96	0.19	533557
Opened email	0.64	0.48	533557
Click	0.25	0.43	533557
Click if opened email	0.36	0.48	340777
Total clicks if click	2.98	3.02	130810
Distinct clicks if click	1.95	1.09	130810
Application if click	0.28	0.45	7423

Table: Descriptive statistics of the main take-up measures among job seekers drawn for treatment. Sample restricted to job seekers who were still unemployed as of 19/11/2019.

ITT on job seekers' job finding



## ITT on job seekers' job finding by gender

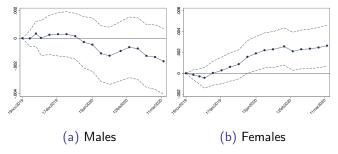


Figure: ITT estimates for job finding at different time horizons for (a) males and (b) females. Sample restricted to job seekers who were still unemployed as of 19/11/2019. Standard errors are clustered at the labor market (Occ.\*CZ) level and associated 95% confidence intervals are displayed.

## ITT on female job seekers' job finding by contract

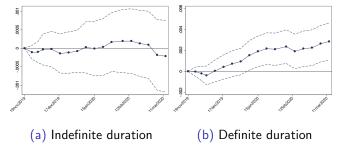


Figure: ITT estimates for females' job finding in (a) indefinite duration and (b) definite duration contracts at different time horizons. Sample restricted to job seekers who were still unemployed as of 19/11/2019. Standard errors are clustered at the labor market (Occ.\*CZ) level and associated 95%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

# Why?

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- Difference is robust to interacting treatment with a rich set of controls and labor market fixed effects.
- ▶ Differential take up: men are roughly 6 percentage points (25%) less likely to open their mail and click on a link.
- Crowding out of search effort among men?
  - Survey evidence that treated men decrease search in other occupations, treated women increase it slightly.
  - Decomposition of effect on job finding by type of firm: treated men *less* likely to be hired by firms that are not identified as "bonnes boîtes."

# Differential take-up: opening emails and clicking on firms' hyperlinks

Table: Gender differences in take-up

	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.

## Survey evidence

We ran a survey on 11,741 randomly selected job seekers (control and treated)

- ▶ Significant increased use of LBB: from 20% to 25 %
- ► Treated men decrease search in other occupations, treated women increase it slightly.
- Treated men decrease number of interviews, treated women increase it slightly.

## ITT decomposition: job finding by type of hiring firm

	Treated firms	Control firms	Other (not BB)	all
		A.	Men	
Treated job seeker	3.449	4.908	14.895	21.797
	(2.922)	(3.459)	(5.701)	(6.611)
Control job seeker	3.377	4.901	15.217	21.963
	(2.892)	(3.457)	(5.752)	(6.629)
Difference	0.072	0.007	-0.322	-0.166
	(0.064)	(0.076)	(0.126)	(0.146)
		B. W	/omen	
Treated job seeker	3.533	5.099	10.468	17.636
	(2.956)	(3.522)	(4.902)	(6.103)
Control job seeker	3.499	5.089	10.286	17.371
	(2.943)	(3.519)	(4.864)	(6.067)
Difference	0.034	0.01	0.181	0.265
	(0.059)	(0.07)	(0.098)	(0.122)

Table: Job finding rates displayed in the last column are decomposed by firm of destination: firms identified as BB and advertised during the experiment (treated firms); firms identified as BB but not advertised during the experiment (control firms); firms not identified as BB (other firms). Rates in %, differences in percentage points.

## Firms' treatment

#### Firms' treatment

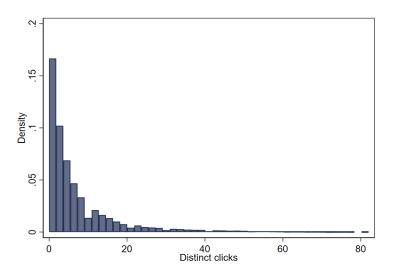
#### Firms' treatment is indirect

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- Specific recommendation links in email
  - ▶ establishments' contacts clicked on average about 14 times by 9 distinct job seekers, implying about one additional application per treated establishment.
- ▶ Increased exposure on the platform during one month
  - ▶ additional 2 clicks (more than ×2).



## Firms' increased exposure

	(1)	(2)	(3)
	Pre intervention	During intervention	Post intervention
ITT	0.0171	1.802	0.0526
	(0.0734)	(0.0702)	(0.0408)
Constant	3.600	1.563	1.700
	(0.0806)	(0.0375)	(0.0411)
N	98366	98366	98366
Mean	3.608	2.469	1.726

Table: Firms' ITT exposure (number of clicks on an establisment's contact info) in LBB's general search results. Standard errors are clustered at the labor market (Sector\*CZ) level.

## ITT on firms' hirings, by contracts

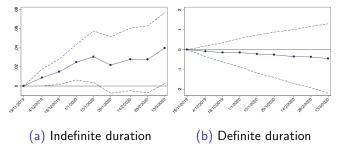


Figure: ITT of total hirings of (a) indefinite duration and (b) definite duration contracts at different horizons controlling for pre-19/11/2019 hirings of registered job seekers in treated CZ. Weighted by inverse treatment status probability. Standard errors are clustered at the labor market (Sec.\*CZ) level. 95% CI displayed.

# ITT on firms' hirings - Comments

► Effect on indefinite duration hirings is stronger in firms which did not have any recorded job offer at PES.

## ITT on firms' hirings - Comments

- ► Effect on indefinite duration hirings is stronger in firms which did not have any recorded job offer at PES.
- Extra hirings of PES job seekers do not appear to reduce hirings of non-PES job seekers.

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- ▶ LBB designed to reduce asymmetric information among job seekers about firms likely to hire in a given occupation, and not necessarily posting jobs (hidden market)
  - ▶ directing search across firms

- ▶ LBB designed to reduce asymmetric information among job seekers about firms likely to hire in a given occupation, and not necessarily posting jobs (hidden market)
  - ▶ directing search across firms
- Potentially larger gains to redirecting search across occupations
  - Recent evidence on occupational mismatch and gains from broadening search (Marinescu & Rathelot 2018, Belot et al. 2018)
  - Mismatch amplified by asymmetric sectoral shock associated with Covid-19 pandemic

- ▶ LBB designed to reduce asymmetric information among job seekers about firms likely to hire in a given occupation, and not necessarily posting jobs (hidden market)
  - ► directing search across firms
- ► Potentially larger gains to redirecting search across occupations
  - Recent evidence on occupational mismatch and gains from broadening search (Marinescu & Rathelot 2018, Belot et al. 2018)
  - Mismatch amplified by asymmetric sectoral shock associated with Covid-19 pandemic
- ▶ Random variation embedded in our two-sided design provides early evidence on the trade-off associated with broadening search: reduced frictions (arbitrage gains across occupations) vs. costs of occupational mobility.

# Occupational distance

- ► For each ROME the relevant expert information on tasks and know-hows is summed in a so called "Fiche métier"
- ► This "Fiche métier" also provides information on potential occupational transitions to "close-by" ROME codes.
- ▶ Putting together the information contained in each of the 532 "Fiche métier" on potential transitions yields a directed graph which we take as our occupational space.
- ▶ We measure occupation distance between two occupations as the shortest path in this graph.

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Note: Working on improved measure for second experiment.

#### Heuristic model

- 1. We recommend firms to workers.
- 2. Workers choose or not to apply to these firms according to occupational distance.
- 3. Firms skim through the applications they receive and randomly decide to look more deeply into some of them. Firms are more or less efficient at screening applications and the screening rate is increasing in a firm's predicted hirings.
- 4. Firm review each selected application and decide whether or not to hire each reviewed applicant according to occupational distance.

# Optimality

- ► The number of recommendations we can make is fixed (i.e. limited number of emails).
- ▶ If possible we want to recommend workers to firm which (1) are close and (2) are predicted to hire a lot.
- Conditional on firms (1) relative occupational distance and (2) level of predicted hirings we do not want to overflow some firms with applications while leaving other empty-handed.

As long as tightness varies across occupations within a commuting zone there is a trade-off between:

- recommending firms that are close-by but which will attract too many "local" job seekers and which will be less likely to hire each one of them.
- recommending firms that are "far-away" but which will receive few job seekers and will be more likely to hire.

#### Introduce randomness...

In a world with perfectly homogeneous job seekers and firms the model would tell you:

- 1. to recommend job seekers to firms which are not too distant in the occupational space,
- to divide job seekers evenly between firms (conditional on a firm's predicted hirings and position in the occupational space).

**Trick:** Modify the individual parameters of the model according to each agent's treatment status in order to generate randomness in:

- the number of times each firm gets recommended
- the occupational distance of pairwise recommendations.

# ...through heterogeneous individual parameters

- Randomly assign which job seeker should receive 4 or 8 recommendations.
- Randomly high (resp. low) distaste for occupational distance to some job seekers implying they should receive close (resp. distant) recommendations.
- Randomly assign high (resp.low) screening efficiency to firms implying that they should receive many (resp. few) recommendations.
- Randomly assign high (resp. low) distaste for occupational distance to firms implying that they should receive close (resp. distant) recommendations.

Draw optimal pairwise recommendations conditional on the randomly selected fundamental parameters of the model. Formal model

# Wrapping up

- 1. We draw a treatment status for every job seeker and every firm (test vs. control).
- We select a set of possible parameter values (low/high distastes for firms/workers, low/high screening efficiency for firms)
- 3. We randomly assign workers and firms to sub-treatment arms  $(2 \times 2 \text{ possibilities in both cases}).$
- 4. We "optimally" draw pairwise recommendations given the joint distribution of job seekers, predicted hirings and parameter values over the occupational space.
- 5. We repeat these steps for each of the 94 treated CZ.

# Estimating the distaste for occupational distance

- ▶ Consider job-seeker/firm pairs for which  $R_{i,j} = 1$ .
- ▶ Possible pair level outcomes  $Y_{i,j}$  are:
  - click
  - application (only available for a subset of connected job-seekers)
  - hire
- ▶ How do these vary according to occupational distance?
- Reduced-form equation from heuristic model:

$$E[Y_{i,j} = 1 | R_{i,j} = 1, d_{i,j}] = \beta_0 \times \beta_1^{d_{i,j}}.$$

 $\blacktriangleright$   $\beta_1$  reduced-form parameter capturing the impact of distaste for distance among job seekers (clicks, applications) and among job seekers and firms (hirings).

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▶  $\beta_1$  reduced-form parameter capturing the impact of distaste for distance among job seekers (clicks, applications) and among job seekers and firms (hirings). ▶  $\beta_0$  and  $\beta_1$  over-identified using firm's and worker's random assignment to far (vs. close) matches.

# Estimating the distaste for occupational distance Main sample

	(1)	(2)
	Click	Hired
0	0.111	0.000640
$\beta_0$	0.111	0.000640
	(0.000471)	(0.0000303)
$eta_1$	0.969	0.865
$\beta_1$	(0.00544)	(0.0732)
	(0.00544)	(0.0732)
Ob	2220124	0220124
Observations	2320124	2320124
Standard orrors i	n paranthacas	·

Standard errors in parentheses

Table: GMM estimates on the full sample of recommended pairs. Standard errors are clustered at the job-seeker level.

### Estimating the distaste for occupational distance

Subsample with information on applications

	(1)	(2)	(3)
	Click	<b>Application</b>	Hired
$eta_0$	0.520 (0.00468)	0.0817 (0.00294)	0.00157 (0.000485)
$eta_1$	0.991 (0.0149)	0.907 (0.0600)	0.104 (1.108)
Observations	36596	36596	36596

Standard errors in parentheses

Table: GMM estimates on the sample of recommended pairs involving job-seekers connected to their online account. Standard errors are clustered at the job-seeker level.

Introduction

La Bonne Boîte

Experimental design and data

Reduced-form results

Structural approach to occupational frictions

Conclusion and road ahead

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- ▶ On firms' side, effect on indefinite duration hirings (4%).
- On both sides our results are compatible with displacement effects.
- ► Evidence of limited distaste for occupational distance: opens room for mismatch reduction?
  - Yet: Our sub-treatment arms do not yield any clear pattern
  - ▶ need to better evaluate trade-off between arbitrage gain and mobility cost? With better measure of occupational distance?

#### Road ahead

- ► Systematic honest heterogeneity analysis using generic machine learning.
- ▶ Modify design to better evaluate potential spillover effects.
- Disentangle frictions on the job seeker's side from frictions on the firm's side: structural model and/or better intermediate outcomes.
- Evaluate the potential to reduce occupational mismatch? To do so need to better measure and control occupational distance.

# Additional material

#### **Predictions**

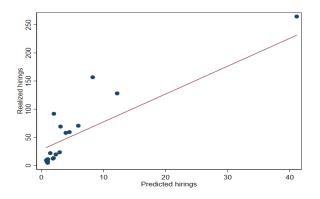


Figure: Realized hirings vs predicted hirings in all CZ. Overall correlation is 0.32 with an R2 of 0.14.



# Accounting

Firms	Job Seekers
445,017	5,441,033
98,366	1,209,859
38,810	806,437
37,467	799,759
	445,017 98,366 38,810

Table: General accounting

Back to strata

# Commuting zones

	min	p25	p50	p75	max	mean	sd	count
Radius	2.2	15.25	19.86	24.75	114.56	20.29	9.61	403
Population	11.7	64.30	102.80	177.50	2234.10	160.05	183.42	403
Job seekers	1163.0	4583.50	7827.00	15338.00	192281.00	13467.90	16685.38	404
Establishments	303.0	2381.00	4339.00	9051.50	217293.00	8389.82	14420.63	404

Back

#### Local slackness

The local slackness ratio of occupation j is defined as the ratio of possible recommendations present in the vicinity of occupation j to the total number of hirings predicted in occupation j:

$$\bar{\theta}_j = \frac{\sum_{w} \rho_w^{d_{i,j}} R_w}{\sum_{f} V^{f,j}}$$

For  $\gamma > 1$  this function is monotonous in  $A^{f,j}/V^{f,j} > 0$  and verifies:

$$\pi_f(0) = 1$$

$$\pi_f(+\infty) = 0$$

What's more  $\pi_f$  has an inflection point at  $s_f \bar{\theta}_j$  so that according to the value of  $s_f$ , firm's f congestion effect will start to quick in either before or after the number of recommendations sent to (f,j) relative to its predicted hirings reaches the local slackness ratio  $\bar{\theta}_j$ .

Functional forms Back to matches

# Screening technology

graphs/screening\_function.png

Functional forms Back to matches

# Choice of $X_w^{f,j}$

 $X_w^{f,j}$  is a vector of covariates which includes the characteristics of the worker/(firm, occupation) pair (w,j),(f,j) among which:

- 1. occupational distance  $d_{i,j}$
- 2. worker w's distaste for occupational distance  $\rho_w$
- 3. firm f's predicted hirings in occupation j:  $V^{f,j}$
- 4. firm f's distaste for occupational distance  $ho_f$
- 5. firm f's screening efficiency  $s_f$ .

In practice we include in  $X_w^{f,j}$  the following combination of observables and randomly allocated structural parameters:

- 1.  $(1 \rho_w \times \rho_f) d_{i,j}$
- $2. s_f$
- 3.  $V^{f,j}$

The rationale for 1. being that if  $\rho_w=\rho_f=1$  we would not want occupational distance to matter at al.  $\beta_s$   $\beta_V$   $\beta_d$ 

#### Parameter selection

#### We select:

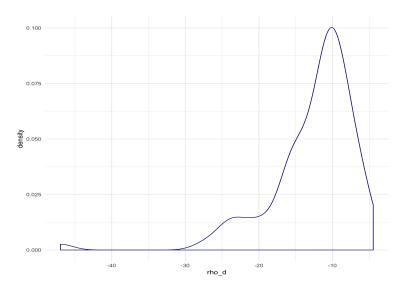
- $ightharpoonup \gamma = 3$
- $s^H = 1.5$  and  $s^L = 0.5$
- $\rho^H = 0.94 \text{ and } \rho^L = 0.82$

The choice of  $\rho^H$  and  $\rho^L$  is guided by the following exercise:

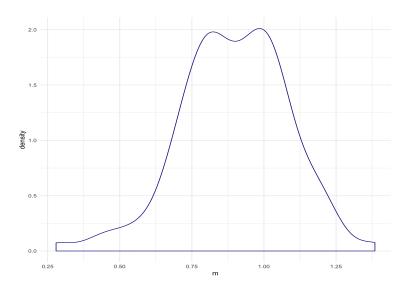
- What is the value of  $\rho^H$  that would make us indifferent between recommending a job seeker to a 6-occupations away high efficiency firm compared to a low efficiency firm which is in his own occupation?
- Given ρ<sup>H</sup> what is the value of ρ<sup>L</sup> which would make us indifferent between sending a high distaste job seeker to 3-occupation away high efficiency low distaste firm compared to a low efficiency firm in his own occupation?



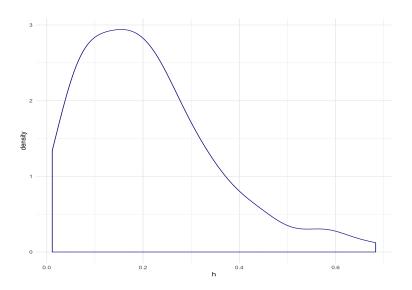
Functional forms



Choice of vector



Choice of vector



Choice of vector

Belot, M., Kircher, P. & Muller, P. (2018), 'Providing Advice to Job Seekers at Low Cost: An Experimental Study on On-Line Advice', (forthcoming)

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