

How can AI improve search and matching? Evidence from 59 million personalized job recommendations

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Motivation and questions

- ▶ The effects of AI on markets (Agrawal et al. 2019, Milgrom and Tadelis, 2018)
 - ▶ (Labour) market intermediaries collect increasingly large data on users' behaviours
 - ▶ AI could be used to help clear markets, as good to sort out heterogeneity
 - ▶ Little is known about whether current AI technologies are mature enough to be used on labour (matching) markets
- ▶ What is the impact of providing job seekers with personalized algorithmic job recommendations on match outcomes?

This paper

- ▶ What we do
 - ▶ We designed a recommender system for job seekers
 - ▶ We partnered with Swedish Public Employment Service to implement it at **national scale**
 - ▶ We designed a **clustered two-sided RCT** to evaluate its impact
- ▶ What we find
 - ▶ Recommender system increases employment by 0.3% at local market level at 5-month horizon
 - ▶ Mechanisms: positive employment effects come from reallocation of applications, rather than increased number of applications
 - ▶ Heterogeneity of treatment effects in dimensions relevant to future policy-making
 - ▶ larger employment effects for less popular jobs and workers with lower job finding rates
 - ▶ scope for occupational broadening

Contributions

- ▶ Algorithmic recommendations in labour markets:
 - ▶ Horton 2017; Belot, Kircher, Muller 2018, 2022; Altmann, Glenny, Mahlsted, Sebald 2022; Behaghel, Dromundo, Gurgand, Hazard, Zuber 2022; Bied, Caillou, Crépon, Gaillac, Perennes, Sebag 2023
- ▶ How do caseworkers help job seekers?
 - ▶ Schiprowski 2020; Cederlöf, Söderström, Vikström 2021
- ▶ Empirical evidence about job search on online platforms:
 - ▶ Kuhn and Skuterud, 2004; Kuhn and Mansour 2014; Faberman and Kudlyak 2018; Marinescu and Rathelot 2018; Hensvik, Le Barbanchon, Rathelot 2021
- ▶ Smart matching
 - ▶ Gee 2019; Fradkin, Bhole, Horton 2023; Arteaga, Kapor, Neilson, Zimmerman 2022; Fack, Grenet, He, Monnet 2023
- ▶ AI in economics
 - ▶ Agrawal et al. 2019; Milgrom and Tadelis 2018; Acemoglu, Autor, Hazell, and Restrepo 2022

Outline

Setting

Market-level results

Worker-level results

Pair-level analysis

Welcome to *platsbanken.se*!

Platsbanken

Lediga jobb för hela Sverige

Sök på ett eller flera ord

 Sök

Ort ▾

Yrke ▾



Job seekers can list vacancies

Platsbanken

🕒 Senaste sökningar ▾

☆ 0 sparade annonser ▾

Sök på ett eller flera ord

umeå personlig assistent



🔍 Sök

Ort ▾

Yrke ▾

Filter ▾

Umeå personlig assistent 🔔 Bevaka

40 annonser med 59 jobb

Sortera efter relevans ▾

Ny

Möjliggörande personlig assistent! Umeå

Lystra personlig assistans - Umeå

Personlig assistent

Publicerad 6 maj, kl. 07.57

☆ Spara

Ny

Personlig assistent sökes till kvinna i Umeå

Aktiv Assistans - Umeå

Personlig assistent

Publicerad 19 maj, kl. 22.15

☆ Spara

Ny

Personlig assistent schemarad 75 % - UMEÅ

TRYGGA ASSISTANS I NORR AB - Umeå

Job seekers can view specific jobs and apply



Translate Spara

Möjliggörande personlig assistent! Umeå

Lystra personlig assistans

Personlig assistent

Kommun: Umeå

Omfattning: Deltid

Varaktighet: 6 månader eller längre

Anställningsform: Tillsvidare- eller tidsbegränsad anställning

Kvalifikationer

Arbetslivserfarenhet

Ingen arbetslivserfarenhet krävs

Om jobbet

Lystra personlig assistans bygger på erfarenhet, kunskap, medvetenhet och trygghet.

Genom att handplocka personal och samarbetspartners med unik kompetens skapar Lystra den trygghet som ger förutsättningar för en kvalitativ personlig assistans. Vi vet att personalen är vår största och viktigaste resurs samt att det är vår uppgift som arbetsgivare att ge alla rätt förutsättningar för att utföra sitt arbete. Lystra personlig assistans skapar kvalitet genom tillit och trygghet för kund och personal. Den tilliten och tryggheten skapar vi genom att respektera varandra och varandras värderingar.

Sök jobbet

Ansök senast 30 juni (om 37 dagar)

Ansök via arbetsgivarens webbplats

Ansök här

Recommendations in practice

 **ARBETSFÖRMEDLINGEN**
SWEDISH PUBLIC EMPLOYMENT SERVICE

Logga in

Az Languages

 Sök

 Meny

🕒 Recent searches ▾

☆ 0 saved ads ▾

Place banks

Vacancies for the whole of Sweden

Search for one or more words

 search

Ort ▾

Profession ▾



Suggestions for you

Environmental and health protection...

Ekerö municipality - Ekerö

Environmental protection officer for t...

Swedish Environmental Protection Agency - Stockholm

Environmental strategist for energy companies...

Jefferson Wells - Stockholm

Quality and environmental manager

Nyckelrekrytering AB - Stockholm

Algorithm

- ▶ Item-to-user collaborative-filtering recommender system with implicit feedback
- ▶ When users click on vacancies, they *implicitly* rate them
- ▶ Input: 30 days of past click history
 - ▶ “naturally occurring” data on such websites
- ▶ Intermediate parameters: unobserved types of each vacancy and of each user (real vectors of dimensions 128)
- ▶ Output: For each user, a set of open vacancies with high type similarity to the user
 - ▶ Decongestion: jobs with more than 200 views are excluded from recommendations
- ▶ Around 10 recommendations generated every night

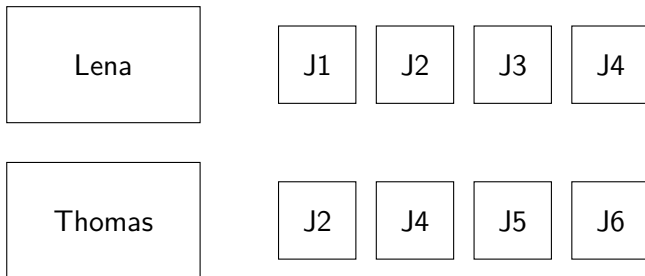
» Formal problem

» Recommended ads

» Ex-ante properties

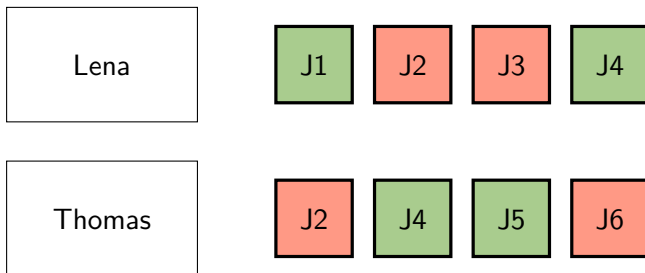
Experimental Design: Example

- Example: Two jobs seekers, with recommended jobs J .



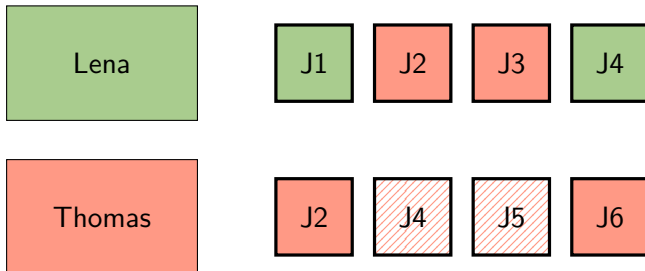
Experimental Design: Example

- ▶ Example: Two jobs seekers, with recommended jobs J .
 - ▶ Half of the recommendations are treated



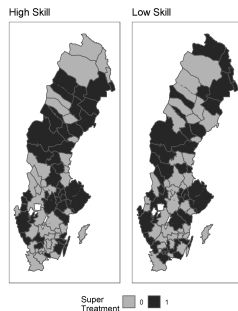
Experimental Design: Example

- ▶ Example: Two jobs seekers, with recommended jobs J .
 - ▶ Half of the recommendations are treated
 - ▶ Half of the individuals are treated



Experimental design

- ▶ Experimental period: April 2021 - March 2022
- ▶ **Two-sided**: both workers and job ads permanently assigned treatment status (50% treatment rate)
- ▶ Treatment
 - ▶ Treated workers see recommendations, control workers do not
 - ▶ Treated ads are displayed in recommendation box
- ▶ **Clustered**: in last 5 months of RCT, we added market-level randomisation (across 138 CZ $\times$ Skill group, excl. Stockholm)



Data

- ▶ Online data
 - ▶ Job ad views: user id, ad id, time
 - ▶ Job applications: user id, ad id, time
 - ▶ Characteristics of job ads posted on Platsbanken: occupation, location, publication date, working hours, posting firm id
- ▶ Register data
 - ▶ Unemployment registers: socio-demographics, start/end dates of unemployment spells, preferred occupations
 - ▶ Linked employer-employee data: monthly earnings for each employee in each company
- ▶ Links
 - ▶ For all registered unemployed (at least once 2019-2022), we match website activity, and unemployment registers and earnings.

Outline

Setting

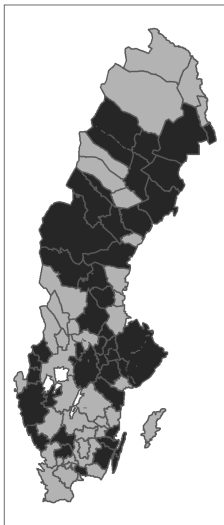
Market-level results

Worker-level results

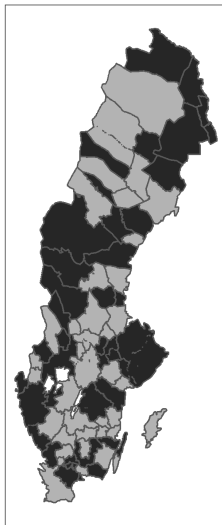
Pair-level analysis

Market-level randomization

High Skill



Low Skill



Super
Treatment

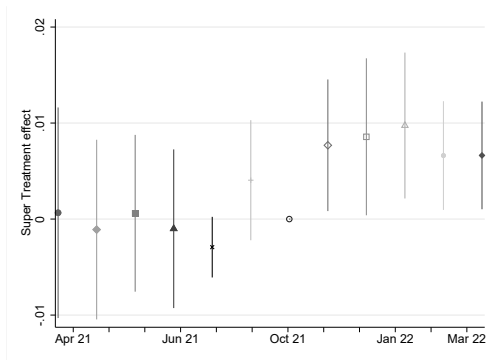
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Market-level treatment effects on employment

- ▶ Market-level randomization for vacancies posted from Nov. 21 to March 22
- ▶ For firm j in local market $m(j)$:

$$\text{LogEmp}_{jt} = \alpha + \delta_t \text{SuperTreat}_{m(j)} + \text{RandPairFE}_{m(j)} + \beta_t X_{jt} + \gamma_t \text{LogEmp}_{j, \text{Oct}21} + \epsilon$$



Controls: pre-exp applications, clicks and employment, full-time, contract types, occupation and industry.
Weighted by firm size in Oct 21.

Market-level heterogeneous treatment effects

	Emp. log RCT end	Hiring Cum	Earnings log RCT end	Vacancy rate Cum
Market is treated	.0066** (.00283)	.217* (.114)	.0085** (.00330)	.0025 (.00855)
Mean dep.		13.6		.594
Weighted No firms	X 26,678		X 26,678	

Controls: pre-experimental applications, clicks and outcome; full-time, contract types, occupation and industry.

►► Unweighted

- Accounting for posting firms share, increase in market-level employment by around 0.3%

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Treatment effect on number of applications

Sample: (i, d) such that job seeker i view at least one ad on day d

Number of daily applications made towards...				
	All jobs	Recommended jobs		
		Yes	Yes but not shown (Control jobs)	No
User is treated	-0.00368* (0.00214)	0.00438*** (0.000132)	-0.000268** (0.000113)	-0.00779*** (0.00201)
Control mean	0.400	0.0143	0.0144	0.371
Pct impact	-0.921	30.66	-1.864	-2.101
Observations	14,605,215	14,605,215	14,605,215	14,605,215
No of users	1.720e+06	1.720e+06	1.720e+06	1.720e+06

» Treat Effect on no of daily clicks

» Registered unemployed

Employment and earnings: Registered unemployed job seekers

	Empl.	Earnings	Empl. dur
Panel A: No controls			
User is treated	0.0039** (0.0020)	5.2 (4.2)	0.0027* (0.0016)
Pct impact	0.64	0.63	0.68
Panel B: all controls			
User is treated	0.0038** (0.0018)	3.7 (3.8)	0.0023 (0.0014)
Panel C: DDML			
User is treated	0.0031* (0.0018)	2.2 (3.7)	0.0017 (0.0014)
Observations	245,209	245,209	245,209
Control mean	0.606	830.4	0.389

Outcome: Employment between randomization month and June 2022: around 6 months on average.

Controls: pre-exp earnings and online search, demographics and education, occ. and muni FE, rand. calendar month.

Outline

Setting

Market-level results

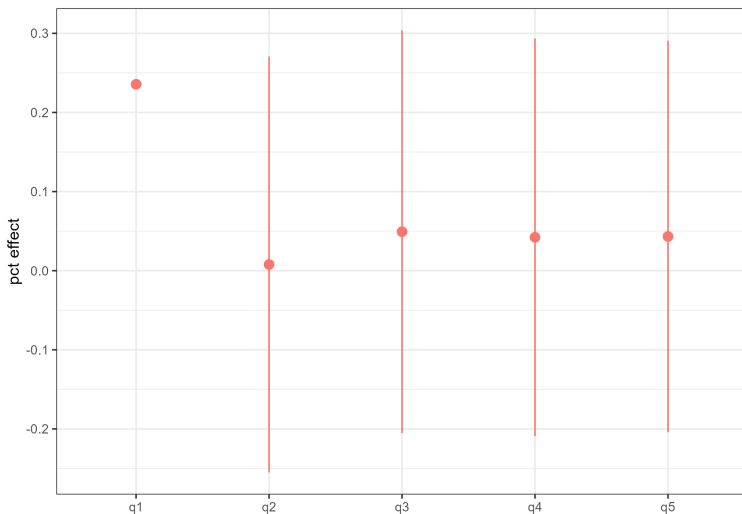
Worker-level results

Pair-level analysis

Pair-level employment effect and heterogeneity

- ▶ Average effect btw fully treated pair (treated worker and treated vac.) and fully control pair (control worker and control vac.) ($E_{TT}/E_{CC} - 1$): 5.5% (p-value = .001) [▶ Table](#)
- ▶ Stronger positive effects for:
 - ▶ less-educated workers
 - ▶ job seekers unemployed at time of assignment
 - ▶ workers who initially looked further away (geog)
 - ▶ vacancies associated with several jobs
 - ▶ older job ads
 - ▶ unpopular vacancies with low # clicks by control users
 - ▶ recommended occupation different from users' reference
- ▶ No significant heterogeneity by worker's gender and age, by vacancy rank in users' set, by # users for whom job recommended

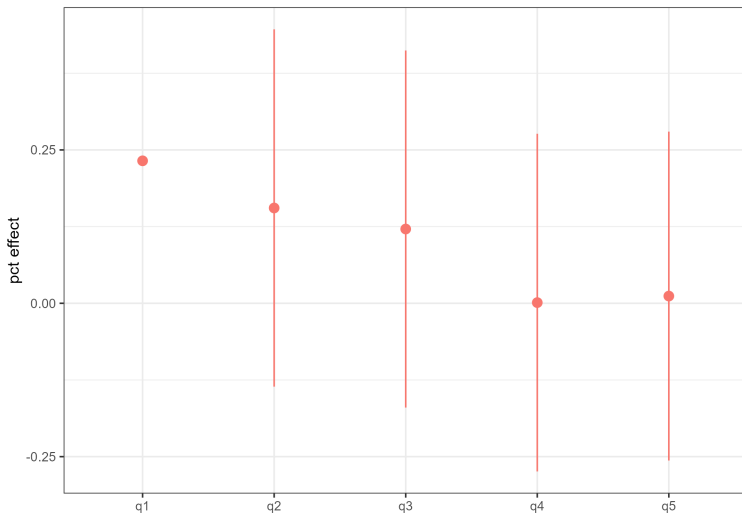
Heterogeneity: Job ad popularity



Popularity: average no of control views during 30 days

» Details

Heterogeneity: Workers predicted job finding



Job finding predicted with workers covariates (incl. education level, U status)

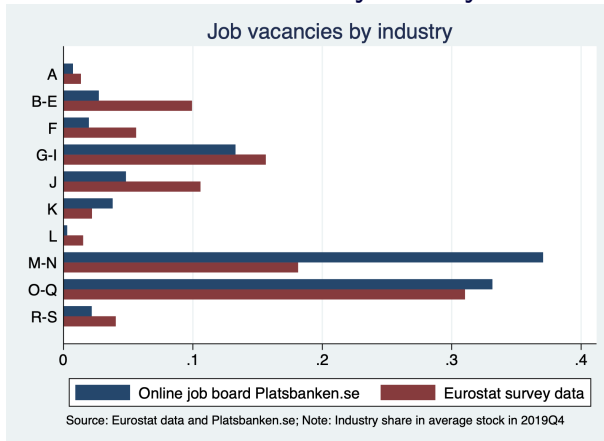
Conclusion

- ▶ Take-aways:
 - ▶ The recommender system **increased market-level firm size** by around 0.3% (with no significant displacement)
 - ▶ The recommender system produced relevant and sensible recommendations which job seekers took seriously: they viewed and **applied** to these recommended ads
 - ▶ Receiving recommendations increased the probability to be **employed** (by 0.6%) due to higher **conversion rates** rather than higher number of applications
 - ▶ Sizeable **heterogeneity of impact**
- ▶ Interpretation + Policy
 - ▶ Low marginal **cost** intervention + portable as relying on **natural** data
 - ▶ Positive results: heterogeneity in recommendations across individuals (**personalization**) likely key to limit congestion and negative externalities
 - ▶ How to increase further efficiency of matching process? How to incorporate in real-time preferences of employers?

Large coverage of *Platsbanken*

- ▶ Any private firms can post online and screen job seekers profile (free of charge)
- ▶ Very large coverage of Swedish vacancies:
 - ▶ Eurostat: 96,569 vacant jobs in 2019Q4 (based on firm survey)
 - ▶ Platsbanken: 92,858 vacancies in 2019Q4
 - ▶ Some differences in industry composition [» Details](#)

platsbanken.se vs. vacancy survey



A: Agriculture, forestry and fishing; B-E: Manufacturing (except construction); F: Construction; G-I: Wholesale and retail trade, transport, accommodation and food service activities; J: Information and communication; K: Financial and insurance activities; L: Real estate activities; M-N: Professional, scientific and technical activities; administrative and support service activities; O-Q: Public administration, defense, education, human health and social work activities; R-S: Arts, entertainment and recreation; other service activities.

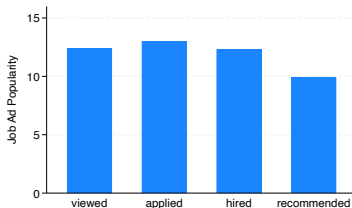
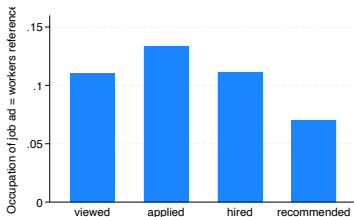
More formally

- ▶ $R(i, j)$: number of clicks by job seeker i on vacancy j
- ▶ $P(i, j) = \text{sign}(R(i, j))$: whether job seeker i clicked on vacancy j
- ▶ X matrix of user types; Y matrix of vacancy types

$$\min_{X, Y} \mathcal{L} = \sum_{i, j} C(i, j) (P(i, j) - X(i, \cdot) Y'(\cdot, j)) + \lambda (\|X\|^2 + \|Y\|^2)$$

- ▶ where confidence is $C = 1 + \alpha R^3$
- ▶ Matching score: $\mathcal{M}(i, j) = X(i, \cdot) Y'(\cdot, j)$ allows to rank all vacancies for a given worker
- ▶ Recommend the highest ranked vacancies for a given user

Recommended ads vs. ads viewed spontaneously (Control workers)



Popularity: # daily clicks received by the vacancy during the first 30 days after publication from control users

» Back

Recommended ads vs. ads viewed spontaneously (Control workers)

Compare average distance btw reference municipality/occupation and clicked/applied/hiring/recommended vacancy

	Spontaneous activity			Recommendations
	clicks	app	emp	all
Geo Dist (km)	50.5	47.0	23.4	46.7
Occ (same 4 digits)	0.110	0.133	0.111	0.077
Popularity	12.4	13.0	12.3	9.9
Days since publication	12.5	12.6	9.9	18.5

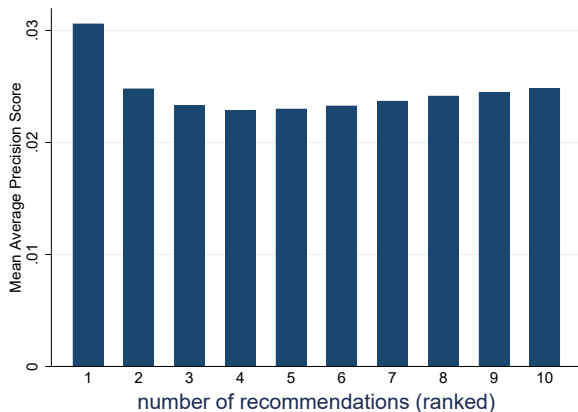
Popularity: # clicks received by the vacancy during the first 30 days after publication from control users

Algorithm properties

- ▶ Relevance (Mean Average Precision)
 - ▶ 3% of active users spontaneously click on the highest ranked vacancy during the day after recommendations are generated
 - ▶▶ Plot
 - for a random vacancy: corresponding stats is 10^{-5}
- ▶ Coverage: 58% of vacancies recommended to at least one user
 - ▶ increases with vacancy popularity (during training period)
 - ▶▶ Plot
 - ▶▶ Plot
- ▶ We exclude from recommendations, vacancies with more than 200 clicks over training period (15% of vacancies)

▶▶ Back

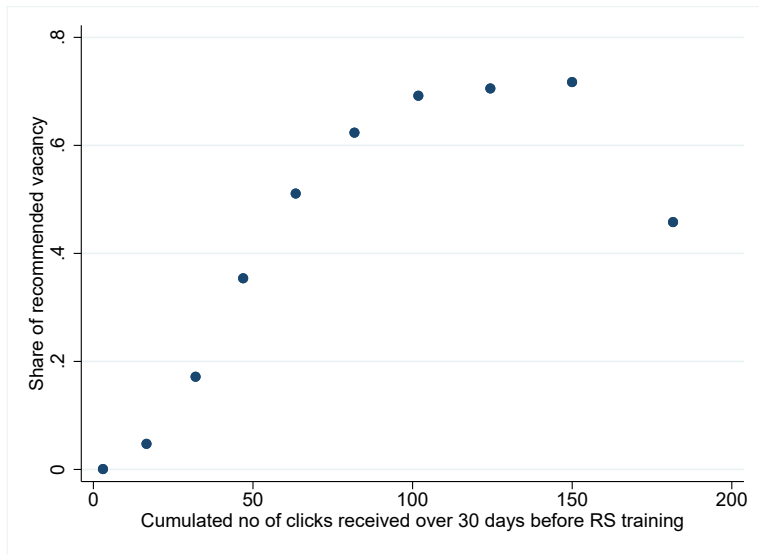
Mean Average Precision



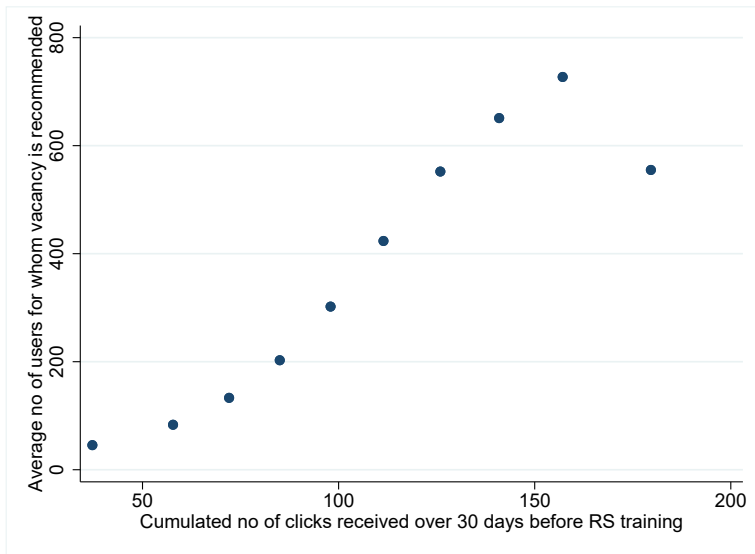
$$MAP(k) = \frac{1}{\min(k, \text{Card}(C(u)))} \sum_{i=1}^k \mathbf{1}[rec(i) \in C(u)] \frac{\sum_{j=1}^i \mathbf{1}[rec(j) \in C(u)]}{i} \quad (1)$$

where $C(u)$ is the # of clicked vacancies in the validation period

Coverage, extensive margin

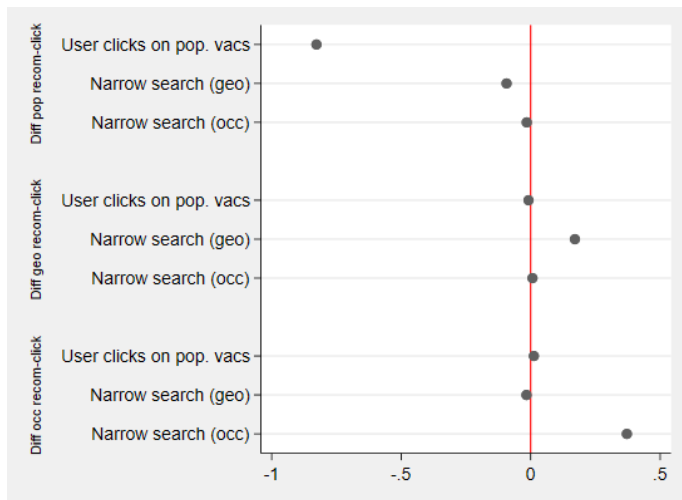


Coverage, intensive margin

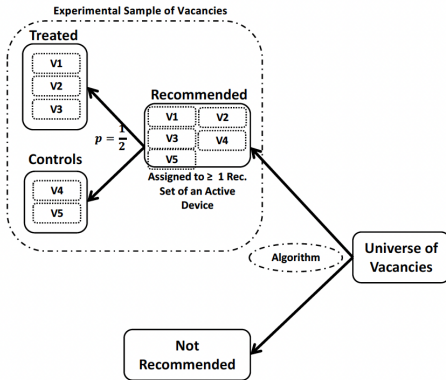
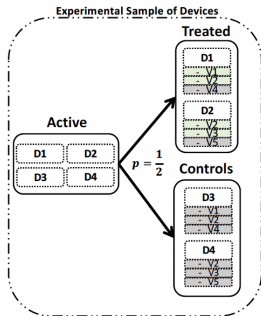


note: out of a daily average of 662,392 jobseekers

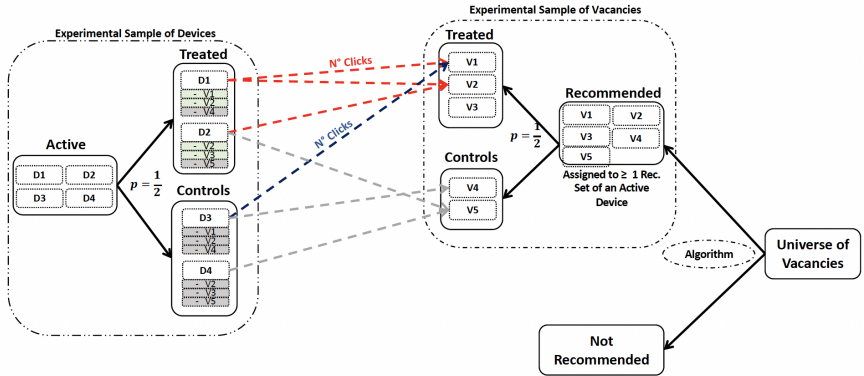
Recommended vacancies vs. clicked vacancies among control users, by worker characteristics



Experimental Design - Treatment Effect (Device – Side)



Experimental Design - Treatment Effect (Device – Side)



Sample scope and size

- ▶ Registered unemployed job seekers: around 250,000 in experiment between April 2021-March 2022
- ▶ Users: around 1.7 million active users in experiment between April 2021-March 2022 (active Platsbanken users)
- ▶ Job postings: around 605,000 included in training set April 2021-March 2022
- ▶ Recommendation sets: 59 million jobs $\times$ job seeker pairs

▶▶ Balancing tests: users

▶▶ Balancing tests: registered unemployed

▶▶ Balancing tests: job ads

Balancing tests: users

Click history during the previous 30 days before first randomisation:

	Treated	Control	diff	pval
Total no clicks	7.538	7.543	-0.005	0.393
No active days	1.671	1.671	0.000	0.812
Average no daily clicks	1.100	1.099	0.000	0.696
Total no applications	3.529	3.531	-0.002	0.883
Average no daily applications	2.189	2.185	0.004	0.272
Average no vacancies clicked	5.317	5.327	-0.009	0.134
region stockholm	0.225	0.225	0.000	0.809
region vastra	0.164	0.165	-0.000	0.905
Open-ended contract	0.631	0.631	-0.000	0.998
Regular employment	0.896	0.895	0.000	0.229
Fixed salary	0.950	0.950	0.000	0.015
Full-time	0.694	0.694	0.001	0.163
Requires experience	0.732	0.731	0.000	0.336
Nurse occ.	0.020	0.020	0.000	0.524
Teacher occ.	0.043	0.043	0.000	0.961
ICT architect occ.	0.018	0.019	-0.000	0.393
Unique users	8.58e+05	8.55e+05	.	.

Balancing tests: users

For variables with multiple values, share of treated-control differences with p-value > 0.05

	Share of p-values > 0.05
Reference occupation	0.95
Reference municipality	0.97

Balancing tests: registered unemployed

	Treated	Control	diff	pval
Women	0.493	0.493	-0.000	0.987
Swedish	0.553	0.555	-0.002	0.313
High-school dropouts	0.245	0.246	-0.001	0.723
High-school diploma	0.420	0.423	-0.002	0.252
Post-secondary educ.	0.335	0.332	0.003	0.128
Stockholm resid.	0.097	0.095	0.002	0.191
<i>Before randomization month</i>				
Monthly earnings	1035.350	1027.866	7.484	0.111
Employment (extensive)	0.768	0.767	0.001	0.513
Employment (intensive)	0.436	0.433	0.003	0.063
Monthly wages	2088.273	2081.858	6.416	0.246
<i>During the 30 days before randomization</i>				
No of days with clicks	3.064	3.039	0.025	0.087
No of clicks	14.163	14.121	0.042	0.574
No of diff. vacancies clicked	12.748	12.719	0.029	0.668
No of days with apps	1.413	1.408	0.005	0.540
No of apps	4.150	4.156	-0.007	0.836
Observations	1.23e+05	1.22e+05	.	.

Balancing tests: registered unemployed

For variables with multiple values, share of treated-control differences with $p\text{-value} > 0.05$

	Share of $p\text{-values} > 0.05$
Reference occupation	0.94
Reference municipality	0.95

SWE has 290 municipalities

There are over 400 4-digit occupational categories

Balancing tests: vacancies

	Treatment	Control	Difference	P-value
Days out before randomization	4.064	4.063	0.001	0.953
Total no of clicks before rand.	72.252	72.341	-0.089	0.420
Average no of daily clicks before rand.	37.949	38.059	-0.110	0.243
Total no of applications before rand.	5.729	5.741	-0.012	0.564
Average no of daily apps before rand.	3.966	3.974	-0.008	0.631
region Stockholm	0.291	0.288	0.003	0.026
region Vastra	0.174	0.176	-0.001	0.126
Open-ended contract	0.682	0.681	0.001	0.567
Regular employment	0.915	0.914	0.001	0.053
Fixed salary	0.931	0.930	0.000	0.462
Full-time	0.773	0.772	0.001	0.292
Requires experience	0.761	0.761	0.000	0.721
Nurse occ.	0.045	0.046	-0.000	0.579
Teacher occ.	0.050	0.050	0.000	0.894
ICT architect occ.	0.050	0.050	-0.000	0.523
Admin and support ind.	0.249	0.248	0.001	0.302
Health and social ind.	0.189	0.189	-0.000	0.942
	3.03e+05	3.02e+05	.	.

Balancing tests: vacancies

For variables with multiple values, share of treated-control differences with $p\text{-value} > 0.05$

	Share of $p\text{-values} > 0.05$
Occupation SSYK4	0.95
Industry	0.95
Publication week	0.97
Municipality	0.95
Commuting zone	0.94
local labor market	0.96

Treatment effect on probability to click on a given day

For job seeker i on day d : $Y_{id} = \alpha + \delta T_i^w + \epsilon_{id}$

	(1) Active	(2) Active
User is treated	0.00027 (0.00022)	0.00052 (0.00063)
Sample	All	Registered User
Observations	178,091,554	26,688,448
Control mean	0.082	0.11
Outcome sd	0.27	0.31
Pct impact	0.33	0.49

Treatment effect on the number of days when vacancy is included in at least one recommendation set

For vacancy j , we run the following regression: $Y_j = \alpha + \delta T_j^v + \epsilon_j$

Days in recommendation set	
Vacancy is treated	0.0342 (0.0600)
Observations	6.05e+05
Control mean	18.85
Outcome sd	18.12

Treatment effect on number of clicks

Sample: (i, d) such that job seeker i view at least one ad on day d

For job seeker i on day d : $Y_{id} = \alpha + \delta T_i + \epsilon_{id}$

	Number of daily clicks/views made towards...			
	All jobs	Recommended jobs		
		Yes	Yes but not shown (Control jobs)	No
User is treated	0.00451 (0.00526)	0.0463*** (0.000417)	-0.00111*** (0.000325)	-0.0407*** (0.00514)
Control mean	3.347	0.105	0.106	3.136
Pct impact	0.1	44.0	-1.0	-1.3
Observations	14,605,215	14,605,215	14,605,215	14,605,215
No of users	1.720e+06	1.720e+06	1.720e+06	1.720e+06

Treatment effect on number of applications - Registered unemployed

Sample: (i, d) such that registered unemployed i view at least one ad on day d

	Number of daily applications made towards...			
	All jobs	Recommended jobs		
		Yes	Yes but not shown (Control jobs)	No
User is treated	-0.010 (0.0069)	0.012*** (0.00049)	-0.00063 (0.00040)	-0.021*** (0.0065)
Control mean	0.88	0.032	0.032	0.82
Pct impact	-1.1	37.6	-2.0	-2.6
Observations	2,839,834	2,839,834	2,839,834	2,839,834
No of users	257,147	257,147	257,147	257,147

Treatment effect on daily clicks received

For vacancy j in day d : $Y_{jd} = \alpha + \delta T_j + \epsilon_{jd}$

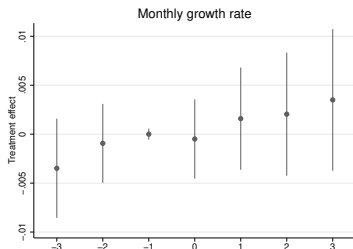
Sample: (j, d) such that job posting j recommended at least once to either a treated or a control job seeker on day d

	Vacancy's number of daily clicks received from			
	All users	users with job in recomm. set		
		all	Treat. users	Cont. users
Vac is treated	0.0953*** (0.0223)	0.0887*** (0.00181)	0.0875*** (0.00103)	-0.00158* (0.000833)
Control mean	8.480	0.360	0.179	0.180
Pct impact	1.124	24.66	48.80	-0.879
Observations	9,078,687	9,078,687	9,078,687	9,078,687
No of jobs	605,114	605,114	605,114	605,114

Firm size

Sample: (f, t) firm f in month t that posted a first experimental job j in month t_0 . Event-study specification around t_0 :

$$\log(Emp_{f(j),t}/Emp_{f(j),t_0-1}) = \sum_{k=-3..3} \mathbf{1}(t = t_0 + k) (\alpha_k + \delta_k \times Treat_j) \\ + \beta X_j + CalendarMonthFE + \epsilon_{f(j),t}$$



- Diff-in-diff specification with $Post = \mathbf{1}(t > t_0)$
- Treatment effect:
 $\hat{\delta} = 0.36^* \text{ log point}$

Controls: occupation, industry, CZxSkill LLM, calendar month. CI at 95%.

► Estimation Table

Average effects on firms

Sample: first experimental job j vacancy by firm f in month t_0
 Diff-in-diff specification with $Post = \mathbf{1}(t > t_0)$:

$$\log(Emp_{f(j),t}/Emp_{f(j),t_0-1}) = \alpha + \gamma Treat_j + \delta Treat_j \times Post_t \\ + \beta X_j + calendarFE + \epsilon_{f(j),t}$$

	Firm Emp. Growth (log)				# vac (log)
# vac	all	1	2-4	5+	
Panel A: no controls					
Vac. is treated x Post	0.00344 (0.00209)	0.00335 (0.00355)	0.00777** (0.00362)	-0.00193 (0.00369)	
Vacancy is treated					0.00629 (0.0109)
Panel B: with controls					
Vac. is treated x Post	0.00360* (0.00208)	0.00328 (0.00353)	0.00819** (0.00358)	-0.00183 (0.00364)	
Vacancy is treated					-0.00222 (0.00820)
Observations	324,765	119,570	108,937	96,258	48,675

Controls: occupation, industry, CZxSkill LLM, calendar month

Market-level treatment effect

	Log # vacancies (Nov.21-Mar.22)			
	All	Firm-level treat intensity		
		Low	Med	High
Panel A: No controls				
Market is treated	0.00382 (0.00875)	0.00770 (0.00911)	0.0316** (0.0139)	-0.0164*** (0.00597)
Panel B: with controls				
Market is treated	-6.65e-05 (0.00574)	0.00393 (0.00754)	0.0187 (0.0141)	-0.00970 (0.00692)
Panel C: DDML				
Market is treated	-9.42e-06 (0.00428)	0.000671 (0.00455)	-0.000436 (0.0116)	-0.00269 (0.00468)
No firms	26,678	9,036	8,734	8,786

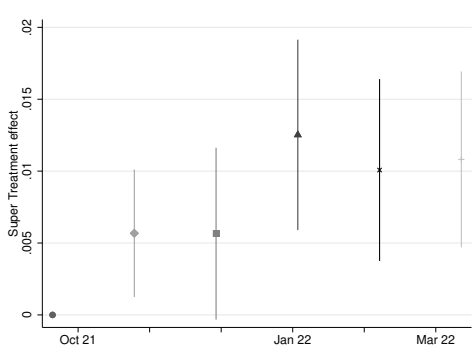
Controls: pre-exp applications, clicks and employment, full-time, contract types, occupation and industry
 Low firm-level treated vacancy share btw 0 and 25%; Med btw 25% and 75%; High btw 75% and 100%.

Market-level treatment effects on employment

- ▶ Market-level randomization for vacancies posted from Nov. 21 to March 22

- ▶ For firm j in local market $m(j)$:

$$\text{LogEmp}_{jt} = \alpha + \delta_t \text{SuperTreat}_{m(j)} + \text{RandPairFE}_{m(j)} + \beta X_{jt} + \gamma \text{LogEmp}_{j, \text{Oct}21} + \epsilon$$

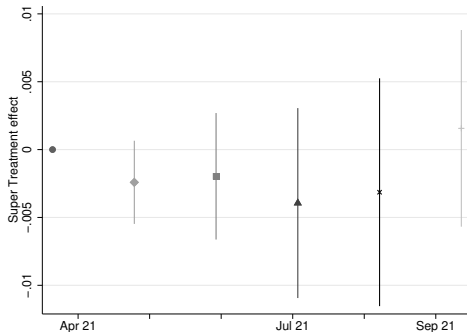


Controls: pre-exp applications, clicks and employment, full-time, contract types, occupation and industry

Market-level PLACEBO effects on employment

- ▶ On previous firm sample, PLACEBO market-level randomization from Mar. 21 to Oct 21
- ▶ For firm j in local market $m(j)$:

$$\text{LogEmp}_{jt} = \alpha + \delta_t \text{SuperTreat}_{m(j)} + \text{RandPairFE}_{m(j)} + \beta X_{jt} + \gamma \text{LogEmp}_{j, \text{Apr}21} + \epsilon$$



Controls: pre-exp applications, clicks and employment, full-time, contract types, occupation and industry. CI at 95%.

Market-level heterogeneous treatment effects

	Log firm employment (RCT end)						
	All	Local tightness		Decongestion		Occ. Broad	
		High	Low	Low	High	Low	High
Market is treated	0.0110*** (0.00309)	0.000871 (0.00267)	0.0176*** (0.00456)	0.00755 (0.00508)	0.0138*** (0.00386)	0.00267 (0.00292)	0.0260*** (0.00649)
No firms	26,678	10,522	16,156	10,692	15,986	17,248	9,430

Controls: pre-exp applications, clicks and employment, full-time, contract types, occupation and industry

- ▶ Local labor market tightness: control applications per job ad
- ▶ Recom Syst decongestion potential: diff btw popularity of recommendations and control views
- ▶ Recom Syst occupational broadening potential: classification occupational distance

▶▶ By treated vac shares

▶▶ Tightness

▶▶ On vacancy posting

▶▶ Joint Heterogeneity Analysis

- ▶ Accounting for posting firms share, increase in emp by 0.3%

Market-level treatment effect

		Log firm employment (RCT end)			
		All	Firm-level treat intensity		
			Low	Med	High
Panel A: No controls					
Market is treated	0.00756 (0.0159)	0.00493 (0.0177)	0.0439* (0.0255)	-0.0217 (0.0226)	
Panel B: with controls					
Market is treated	0.0110*** (0.00309)	0.00836 (0.00506)	0.0157*** (0.00481)	0.00996* (0.00517)	
No firms	26,678	9,036	8,734	8,786	

Controls: pre-exp applications, clicks and employment, full-time, contract types, occupation and industry
 Low firm-level treated vacancy share btw 0 and 25%; Med btw 25% and 75%; High btw 75% and 100%.

Market-level treatment effect

	Log firm employment (RCT end)		
	All	Local tightness	
		High	Low
Panel A: No controls			
Market is treated	0.00756 (0.0159)	0.0500* (0.0282)	0.00597 (0.0153)
Panel B: with controls			
Market is treated	0.0110*** (0.00309)	-0.00119 (0.00267)	0.0173*** (0.00449)
Panel C: DDML			
Market is treated	0.00696** (0.00284)	-0.00228 (0.00219)	0.00936*** (0.00339)
No firms	26,678	10,098	16,580

Controls: pre-exp applications, clicks and employment, full-time, contract types, occupation and industry
 Low tightness if firms belong to local market with average no of applications per ad higher than median.

Market-level heterogeneous treatment effects

- Median split of local labor markets by Recom Syst decongestion potential (diff btw popularity of recommendations and control views), and by Recom Syst occupational broadening potential

	Log firm employment (RCT end)		
High Decongestion X Treated Mkt	0.00641 (0.00619)		0.00512 (0.00564)
High Occ. Broad. X Treated Mkt		0.0233*** (0.00712)	0.0230*** (0.00709)
Treated Market	0.00714 (0.00486)	0.00278 (0.00295)	-0.000194 (0.00369)
No firms	26,678	26,678	26,678

Controls: pre-exp applications, clicks and employment, full-time, contract types, occupation and industry

Pair-level analysis

	Applications	Employment
T worker, T job (α_{11})	0.0123*** (2.93e-05)	0.000490*** (5.85e-06)
T worker, C job (α_{10})	0.00993*** (2.62e-05)	0.000450*** (5.57e-06)
C worker, T job (α_{01})	0.0102*** (2.69e-05)	0.000457*** (5.70e-06)
C worker, C job (α_{00})	0.0102*** (2.66e-05)	0.000464*** (5.67e-06)
Pair-level effect ($\alpha_{11} - \alpha_{00}$)	0.00211*** (3.87e-05)	2.56e-05*** (8.02e-06)
Observations	59,243,200	59,243,200

Net employment effect and congestion

Component	Estimate	p-value	Comment
Effect T jobs	0.035 (0.009)	0.000	$(E_{TT} - E_{CT})/2E_0$
Effect C jobs	-0.015 (0.008)	0.075	$(E_{TC} - E_{CC})/2E_0$
Net effect	0.02 (0.012)	0.103	Sum of row 1 and 2
Congestion g	0.014 (0.017)	0.401	$1 - E_{CT}/E_0$

Market-level heterogeneous treatment effects

	Log firm employment (RCT end)						
	All	Local tightness		Decongestion		Occ. Broad	
		High	Low	Low	High	Low	High
Market is treated	0.0110*** (0.00309)	0.000871 (0.00267)	0.0176*** (0.00456)	0.00755 (0.00508)	0.0138*** (0.00386)	0.00267 (0.00292)	0.0260*** (0.00649)
No firms	26,678	10,522	16,156	10,692	15,986	17,248	9,430

Controls: pre-exp applications, clicks and employment, full-time, contract types, occupation and industry.
Unweighted.

- ▶ Local labor market tightness: control applications per job ad
- ▶ Recom Syst decongestion potential: diff btw popularity of recommendations and control views
- ▶ Recom Syst occupational broadening potential: classification occupational distance

▶▶ By treated vac shares

▶▶ Tightness

▶▶ On vacancy posting

▶▶ Joint Heterogeneity Analysis

Heterogeneity: Model

Subsample of fully treated pairs and fully control pairs:

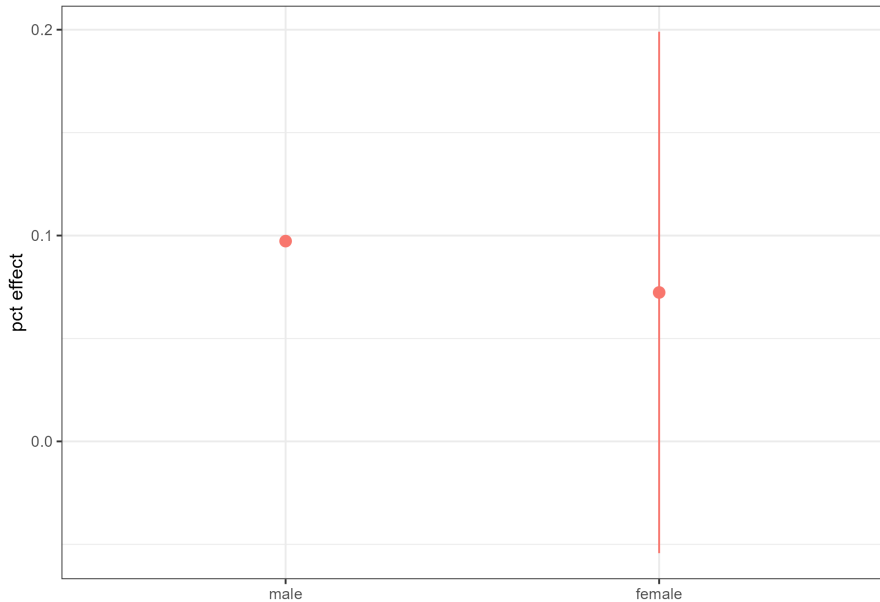
$$Y_{ij} = \sum_l \sum_{k \in \mathcal{K}_l} \delta^{l,k} \mathbf{1}[X_{ij}^l = k] T_{ij}^p + \sum_l \sum_{k \in \mathcal{K}_l} \beta^{l,k} \mathbf{1}[X_{ij}^l = k] + \varepsilon_{ij} \quad (2)$$

where T_{ij}^p indicates whether pair (i, j) is treated, and $\mathbf{1}[X_{ij}^l = k]$ is a dummy indicating whether covariate X^l measured at the level of pair (i, j) is equal to k .

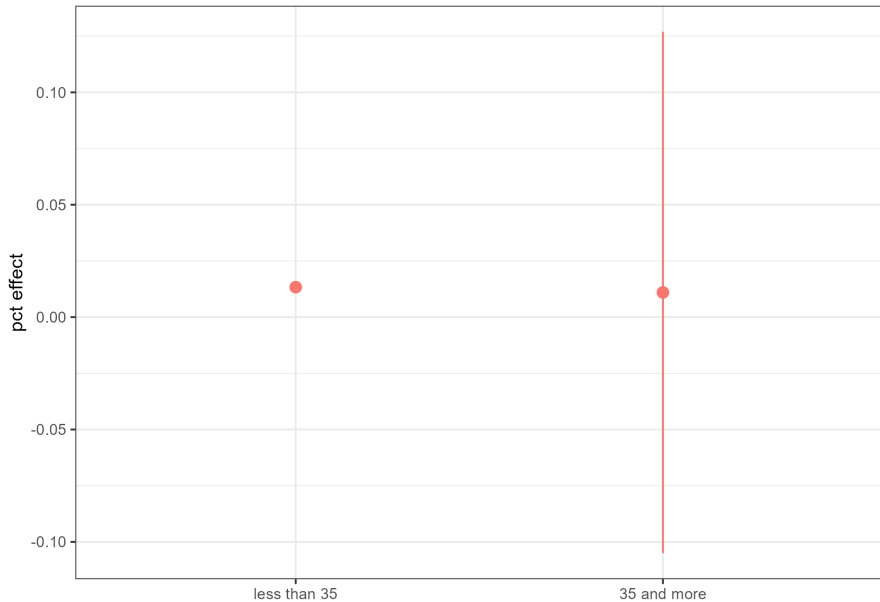
Standard errors clustered at both worker level and job ad level

We plot $\delta^{l,k} / E[Y_{ij} | X_{ij}^l = k]$ in percent, and we test $\hat{\delta}^{l,k} = \hat{\delta}^{l,k_0}$.

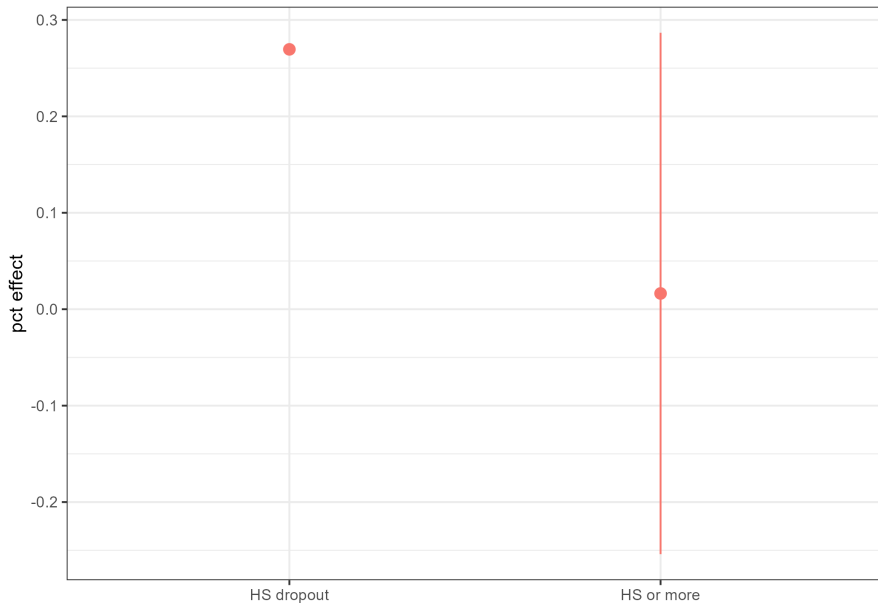
Heterogeneity: gender



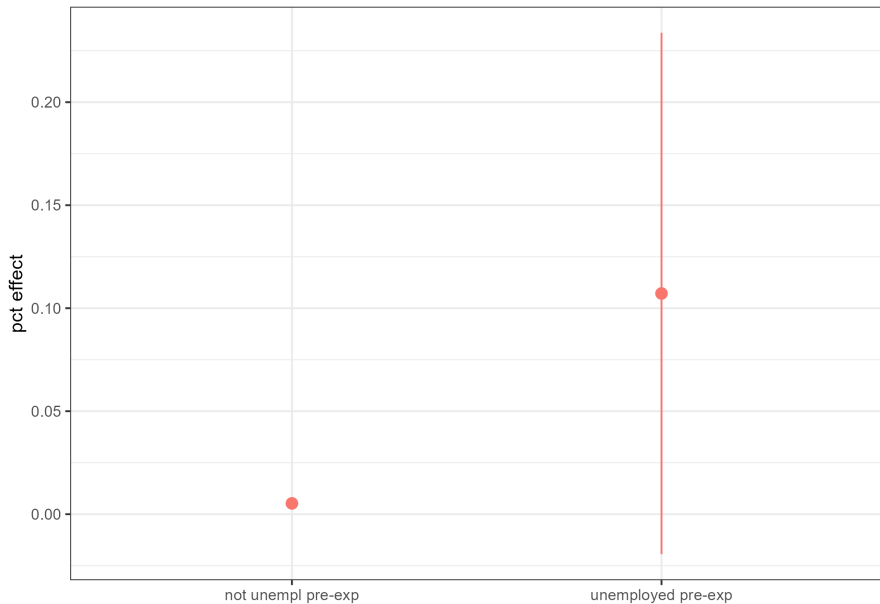
Heterogeneity: worker's age



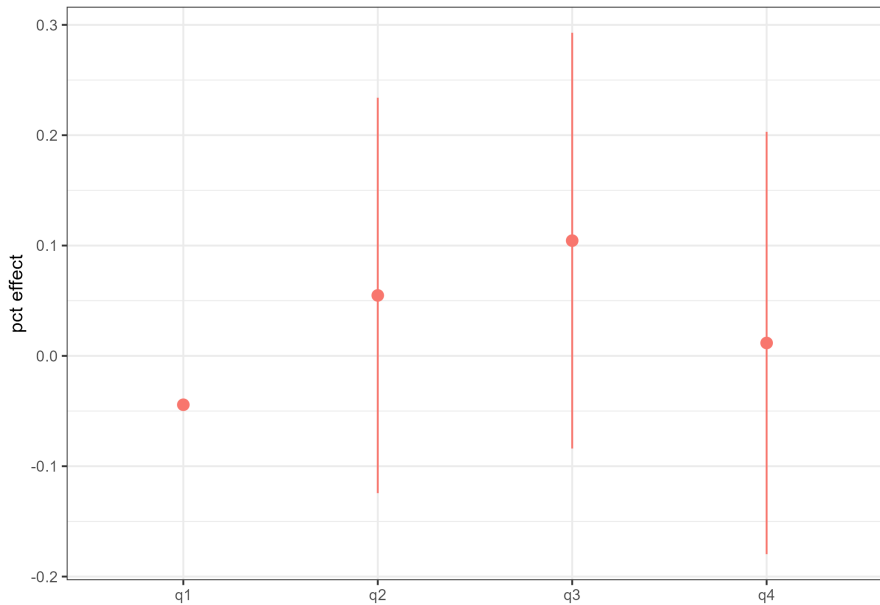
Heterogeneity: education



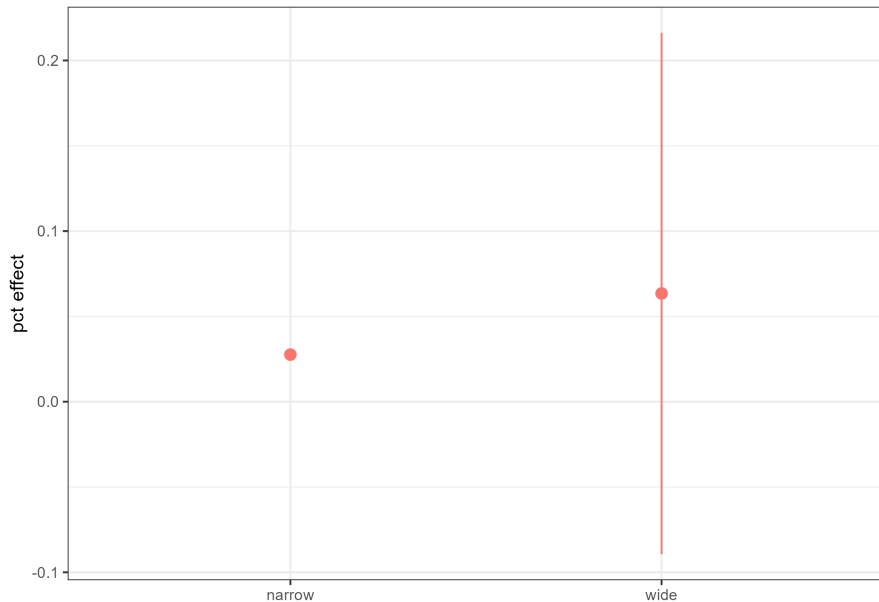
Heterogeneity: initially unemployed



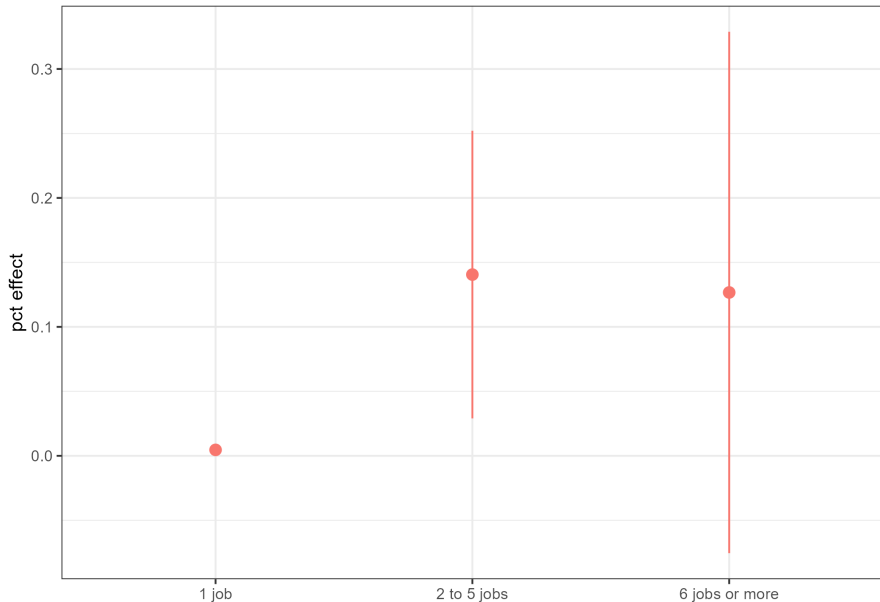
Heterogeneity: Geog. breadth (pre-exp search)



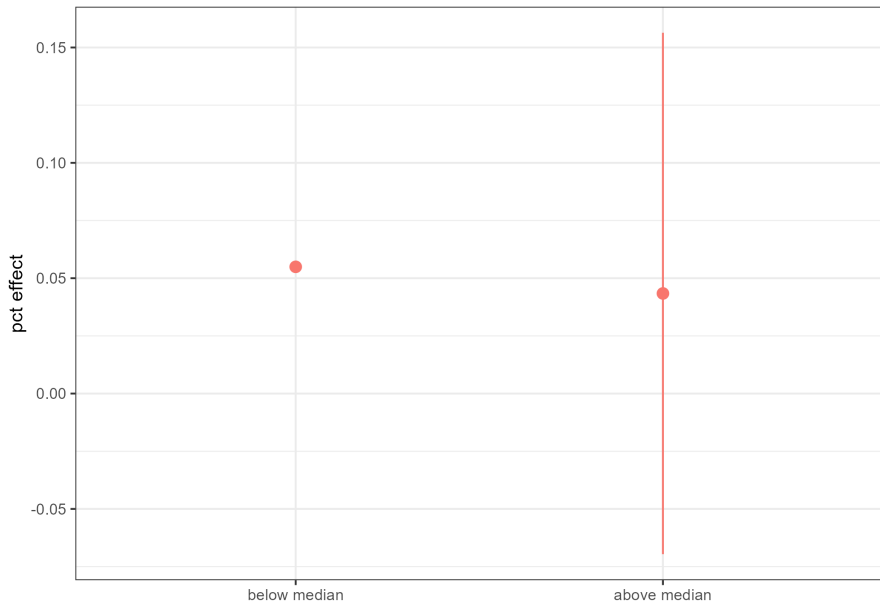
Heterogeneity: Occ. breadth (pre-exp search)



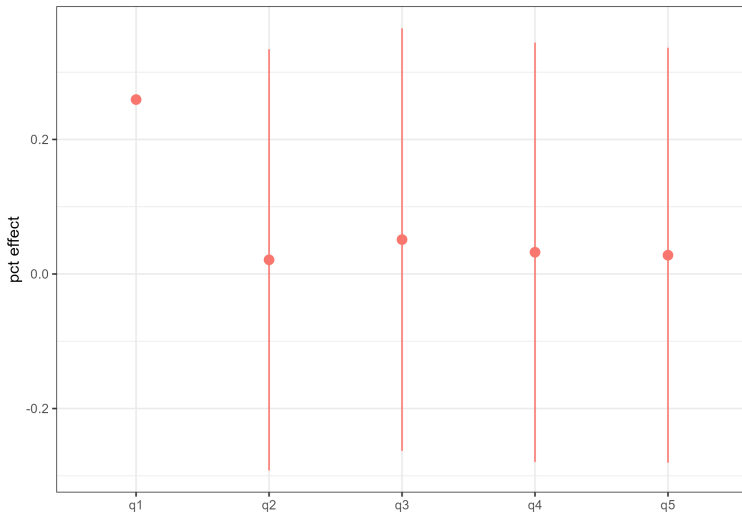
Heterogeneity: nb jobs on job ad



Heterogeneity: nb users that job ad is recommended to

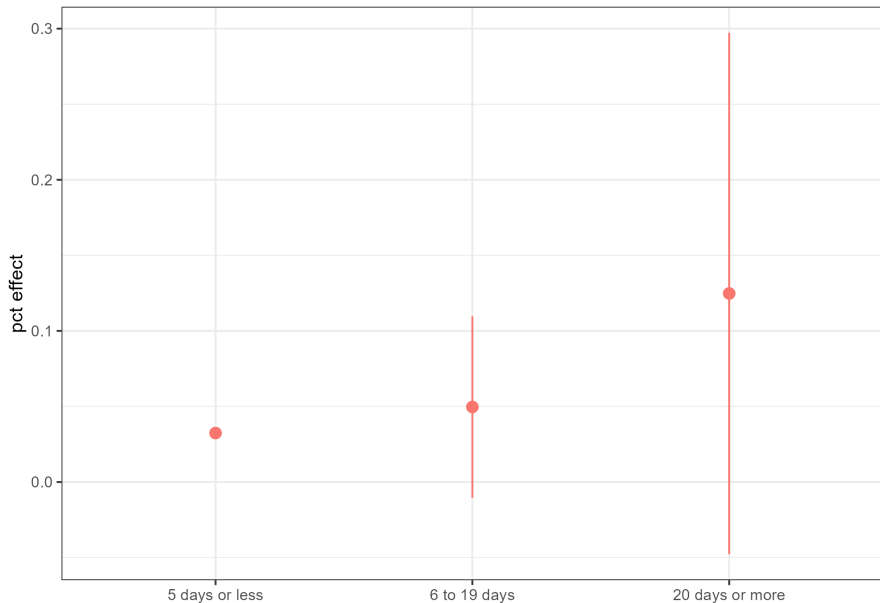


Heterogeneity: Job ad popularity

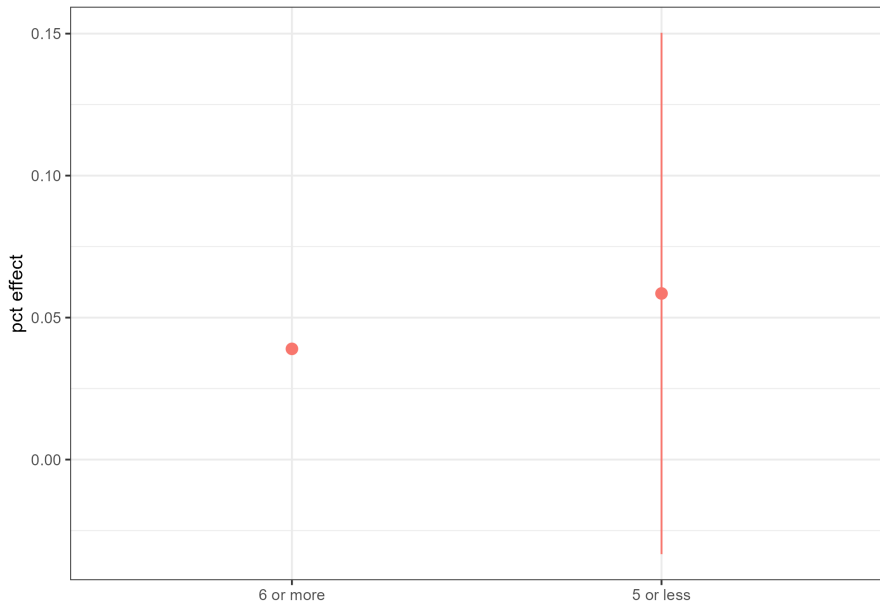


Popularity: average no of control views during 30 days

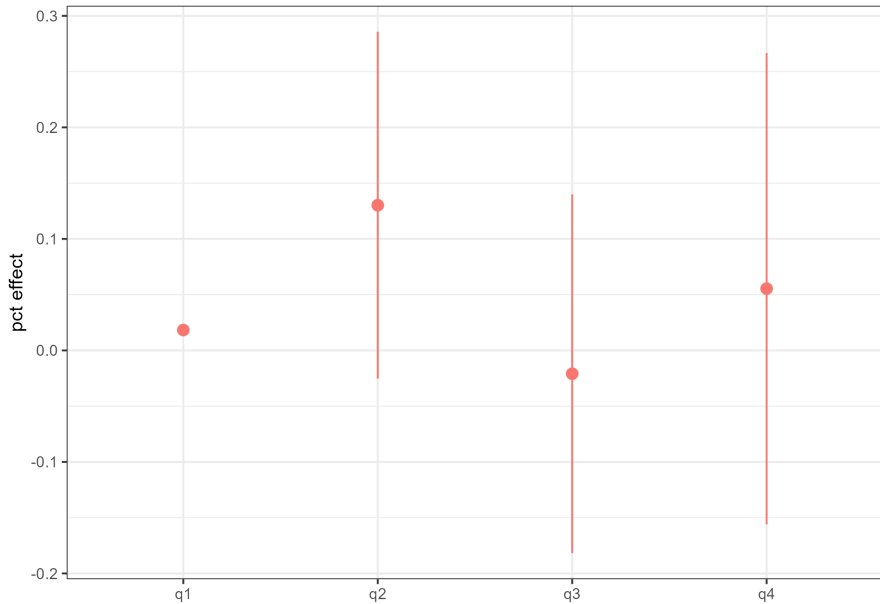
Heterogeneity: Time since ad published



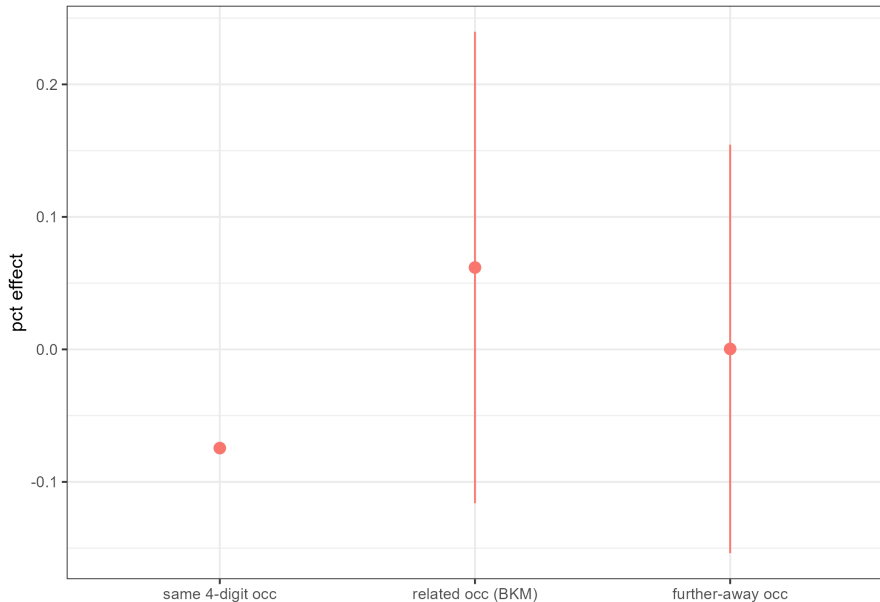
Heterogeneity: Rank of ad in user's recommended set



Heterogeneity: Geog distance between user and job



Heterogeneity: Occ dist between job and user's reference



Heterogeneity: Model 2

Subsample of fully treated pairs and fully control pairs:

$$Y_{ij} = \sum_d \sum_{q \in Q_d} \delta^{d,q} \mathbf{1}[Z_{ij}^d = q] T_{ij}^p + \sum_d \sum_{q \in Q_d} \beta^{d,q} \mathbf{1}[Z_{ij}^d = q] + \sum_l \sum_{k \in K_l} \beta^{l,k} \mathbf{1}[X_{ij}^l = k] + \varepsilon_{ij} \quad (3)$$

where T_{ij}^p indicates whether pair (i, j) is treated, and $\mathbf{1}[X_{ij}^l = k]$ is a dummy indicating whether covariate X^l measured at the level of pair (i, j) is equal to k .

In model 2, we focus on two covariates: quantiles of job ad popularity and of predicted job finding probability Z_{ij}^d .

Standard errors clustered at both worker level and job ad level