

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

By Thomas Le Barbanchon, Lena Hensvik & Roland Rathelot (BHR)

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Andreas Kostøl (ASU)

Research literature on online labor market matching

Internet has changed how workers and firms search for one another

- ▶ Autor's "Wiring the Labor Market", Krueger's NYT article in 2001, and Kuhn & Skuterud in 2004
(Stevenson 2009, Kroft & Pope 2014, Kuhn & Mansour 2014, Hjort & Poulsen 2019, Denzer et al., 2020, Gürtzgen et al., 2022 ++)

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1. reducing amount of search frictions: contact rates \uparrow
2. lowering costs of search and recruitment: search intensity \uparrow

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→ potentially **reinforcing 1+2**, possibly **mitigating congestion problem 3**

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Can we engineer recommendation systems to get people back to work and fill vacant positions?

Why We Care and the Most Closely Related Work

Well-established fact: search is concentrated in own occupation and location

- ▶ concern that congestion lowers employment: mainly addressed through quantitative exercises
(e.g., Nickell 1982, Sahin, Topa, Song, Violante 2014, Patterson, Sahin, Topa, Violante 2016, Marinescu & Rathelot 2017)
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Providing Advice to Jobseekers at Low Cost: An Experimental Study on Online Advice by Belot, Muller, Kircher (Review of Economic Studies 2019)

- ▶ use theory to design automated job search assistance system
 - recommendations from job flows and ONet-similarities + visualizing labor market tightness
- ▶ combined w/ lab-in-the-field experiment (N=300) and survey of activities & outcomes
 - advice causes search \leftrightarrow , interviews \uparrow , imprecise impacts on employment

Questions from BKM and The Contributions of This Paper (LBHR)

Questions from BKM:

- ▶ what conclusions are missed due to lack of statistical power?
- ▶ do higher job finding rates come at the cost of lower match-quality?
- ▶ how do recommendations and broadening search affect (aggregate) congestion?

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Main contributions: first large-scale evaluation of a recommendation system

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- ▶ expanding by offering first evidence on effects of recommendations for vacancy outcomes

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Potential scope: understanding how recommendation system can be used for market design

(connecting paper closer to the discussion of Milgrom & Tadelis 2019)

Trends: AI and Labor Market Matching

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OECD (2023) document increasing use of AI in labor market matching

- ▶ writing job descriptions, applicant sourcing, analyzing CVs
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Adoption of AI tools for labor market matching among large employers

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→ worth examining whether effects are stronger among small firms, who get AI for free?

Industry: AI on Job Platforms in the US

Hello, what would you like to explore today?

For Employers

Post Jobs



Jobs



Companies



Salaries



Careers



andreas.r.kostol@gmail.com

Assistant Professor

Tempe, AZ (US)

Getting the Most of Your Glassdoor



Shining a Light on Equity

Jobs Recommended for You

Recommendations are based on your [profile](#), [job preferences](#), and activity on Glassdoor.



Harkins Theatres
Santan Village 16 - Team Member

3.6 ★

Gilbert, AZ

\$32K - \$41K (Glassdoor Est.) ⓘ



9d



Harkins Theatres
Queen Creek - Team Member

3.6 ★

Queen Creek, AZ

\$31K - \$40K (Glassdoor Est.) ⓘ



9d



Pizza Hut
Team Member

3.5 ★

Mesa, AZ

\$14 - \$15 Per Hour (Employer Est.) ⓘ



Easy Apply 1d



Torchy's Tacos
Front of House Team Member - New Restaurant Opening

3.7 ★

Gilbert, AZ

\$20 - \$20 Per Hour (Employer Est.) ⓘ



Easy Apply 89d

[See all jobs >](#)

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Thanks to Aaron Terrazas at Glassdoor for sharing views

LBHR: “vacancy clicks as input, making it transferable to most other online job boards.”

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Potential for growth of AI in labor market matching?

- ▶ use of large language model for experimentation and ad targeting

Exploratory vs. Specific Search

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- ▶ exploratory phases of the search process, then offering some breadth will help [...] learn their tastes and the options available
- ▶ [...] driven to [sell] something particular, offering a narrower set of [buyers] that match the [worker's skills and] preferences would be better

→ AI can play role in understand the intent of labor market search

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Does Platsbanken-algo pick up differential intent of young vs. long-tenured?

Relatedly, authors explore match quality effects but find little effects – on average

- ▶ worth exploring differential match quality effects among non- vs. specialized workers?

Questions: Missed Opportunities for Market Design?

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...risk of collaborative-filtering recommender system is [...] recommend to many users the same popular item [...thereby exacerbating] congestion. To control that risk, we filter out from the recommendation sets vacancies that received more than 200 clicks over the training period (around 15% of the most popular vacancies).

- ▶ BKM (and LinkedIn) includes tightness in recommendations
- ▶ missed opportunity to learn about AI's ability to **solve a problem?**

Maybe next round of experiments can include the number of clicks / applications?

Final Remarks + Offline Material

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1. Does the recommendation system reduce mismatch (in VU-ratios)?
2. No creation responses from firm-level vacancy-recommendations. What about market-level responses using super-controls?
3. What about other search channels? BML find reallocation to be important.
4. Why clicks and not flows? What is the advantage of not only focussing on occupational flow / characteristics?
5. Personalized rather than occupational-specific recommendations: how much more personal is it with 128 types vs. 300 occupations?