

How migrants search for jobs: Do they undershoot and should they?

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Motivation

- ▶ **Two keys empirical facts from the literature:**

- ▶ Earnings gap (at hiring) between migrants and natives
- ▶ Migrants stay longer unemployed

- ▶ **How do those gaps arise?**

1. Migrant-native gaps in probability to be hired (conditional on applying)
... differential across low- and high-wage jobs
2. interact with under-optimal job search behaviour
... differential between migrants and natives

- ▶ **Idea of this paper:**

1. Document these two mechanisms in observational data
2. Explore causally whether migrants undershoot when applying to jobs

What we do and find

1. Descriptive part: Document the migrant-native differential in job search using job-search data from Sweden (*platsbanken.se*)

↪ What we find:

- a. Migrants search more intensively but have a significantly lower probability to be hired
- b. Migrants apply to firms and occupations that pay less
- c. The gap in applications is larger than in hiring

What we do and find

2. Provide suggestive evidence on migrants' undershooting in a simple application model

- ▶ Compare the application pattern to the return of this application (earnings and hiring probability)

↪ What we find: At the bottom of the income distribution, compared to natives, migrants tend to undershoot

3. Causal evidence from two-sided RCT of job recommender system

- ▶ Study the effect of being randomly assigned to “better vacancies”

↪ What we find: Larger compliance, favourable effects for migrants

Contributions

1. Earnings and employment gaps between migrants and natives (Algan, Dustmann, Gritz and Manning, 2010; Duleep, 2015; Gérard, Lagos, Severnini, Card, 2021; Friedrich, Laun and Meghir, 2022)
2. Difference in hiring probability between migrants and natives (Aslund, Hensvik and Skans, 2014, Aslund, Bratu, Lombardi and Thoreson, 2025)
3. Job search differences across various workers type (Fluchtmann, Glenny, Harmon and Maibom, 2024; Cortes, Pan, Pilossoph, Reuben and Zafar, 2023; Philippe and Skandalis, 2024; Faberman, Mueller, Şahin, and Topa, 2026)
4. Information frictions and misperceptions in job search (Mueller and Spinnewijn, 2023; Caliendo, Mahlstedt, Schmeisser and Wagner, 2023).

↪ Contribution: Focus on **job search** of migrants, and how it influences earnings gap and gap in probability to be hired

Outline

Setting and data

Differences in re-employment outcomes and job search

Application model

Experimental evidence from job recommendations

Welcome to *platsbanken.se*!

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Lediga jobb för hela Sverige

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Job seekers can list vacancies

Platsbanken

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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

Data sources

- ▶ **Online Data** (June -20 to June -22):
 - ▶ Universe of job vacancies posted on Platsbanken (Arbetsförmedlingen)
 - ▶ Online job search activity by unemployment-registered job seekers on Platsbanken (Arbetsförmedlingen)
- ▶ **Register data:**
 - ▶ Universe of unemployment spells (Arbetsförmedlingen)
 - ▶ Matched employer-employee data on monthly frequency (SCB)
 - ▶ Occupation earnings computed from wage and occupation register (SCB)
- ▶ **Links and outcomes:**
 - ▶ For all registered unemployed, we can match website activity with admin data: information on hiring
 - ▶ For each vacancy, we compute earnings occupation fixed effects and firm fixed effects using yearly wage registry from 2015-2019

Details

Summary statistics: job seekers

	Developed	Developing	Natives
<u>Characteristics</u>			
Men	0.44	0.48	0.47
Age	41.00	38.77	41.48
<u>Education</u>			
Less than HS	0.13	0.18	0.10
High school	0.41	0.41	0.47
Some college	0.35	0.31	0.31
College or more	0.11	0.10	0.12
<u>Reference occupation</u>			
Cleaners	0.08	0.07	0.02
Waiters	0.05	0.07	0.02
Warehouse	0.03	0.06	0.02
Grocery	0.02	0.04	0.02
Child Care	0.03	0.03	0.03
Personal Care	0.02	0.03	0.04
Number job seekers	39,887	97,469	192,400

Summary statistics: job seekers

	Developed	Developing	Natives
<i><u>Migrants:</u></i>			
Year since arrival	15.47	11.58	-
<i><u>Migration reason</u></i>			
Labor	0.07	0.03	-
Refugee	0.14	0.42	-
Family	0.36	0.38	-
Other	0.13	0.09	-
Missing	0.29	0.06	-
Number job seekers	39,887	97,469	192,400

Countries of origin

Outline

Setting and data

Differences in re-employment outcomes and job search

Application model

Experimental evidence from job recommendations

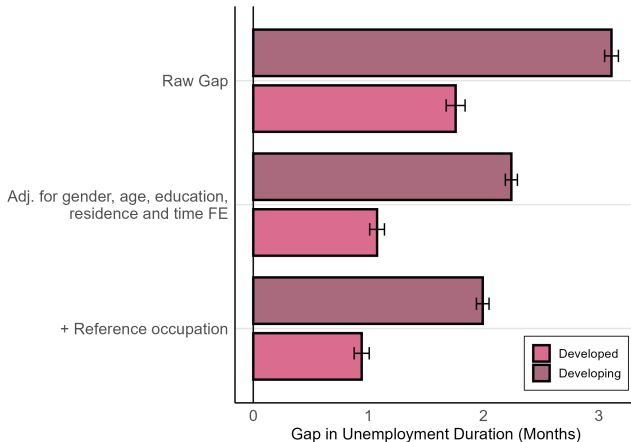
Differences in re-employment outcomes: Methodology

- ▶ **Approach:** OLS regression at individual i , spell level s

$$Y_{is} = \alpha + \beta_1 1[\textit{Developed}] + \beta_2 1[\textit{Developing}] + X_i \delta + X_s \gamma + \varepsilon_{ij}$$

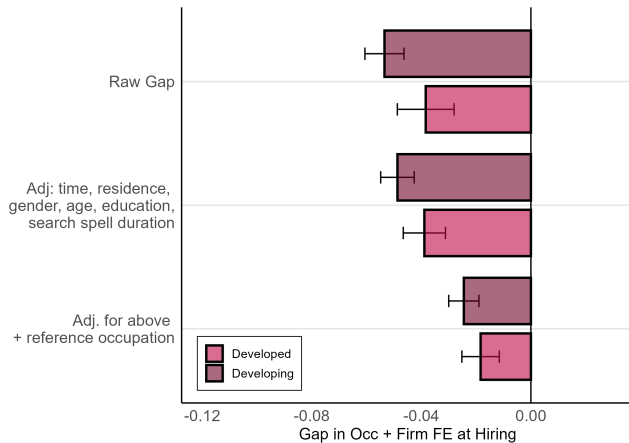
- ▶ Specification 0: Raw gap, no controls
- ▶ Specification 1: $X_i = \{\text{gender, age, education level and field, nb months since spell started, age, 6,000 "neighborhoods" of residence}\}$, $X_s = \text{year-month start of the spell}$
- ▶ Specification 2: Spec 1 + 4-digit reference occupation (declared at registration)
- ▶ **Outcomes:**
 - ▶ Unemployment duration in months
 - ▶ Re-employment earnings
- ▶ **Sample:**
 - ▶ empl. duration: 347,387 spells for 317,681 workers
 - ▶ earnings: 205,904 spells for 193,830 workers.

Unemployment duration gap



Note. Average unemployment duration for natives: 9.5 months

Earnings gap at hiring



Differences in job search: Motivation

- ▶ Interesting to document job-search differentials
- ▶ Do migrants and natives search optimally? And can search differentials explain migrant-native gaps?
 - ▶ Unemployment duration:
 - Could be simply due to difference in hiring probability
 - Or could also be partly explained by search intensity
 - ▶ Earnings gap:
 - Migrants face lower hiring chances in higher paying jobs
 - Or could be that migrants apply to jobs that pay less

↪ A first step to understand whether job search affects the gap is to document job search differentials

Differences in job search: Methodology

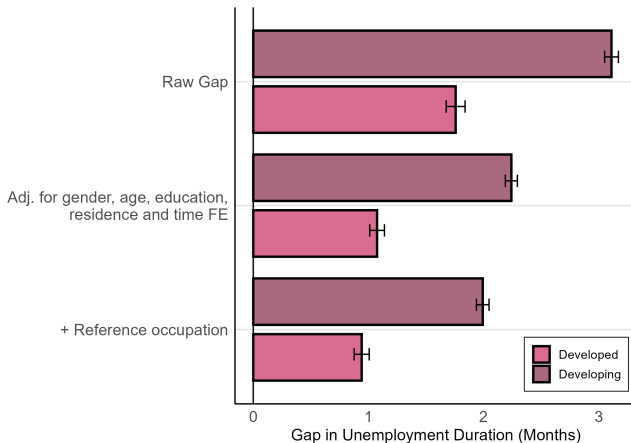
- ▶ **Aim:** Document the differential in applications between migrants and natives regarding:
 - ▶ job search intensity
 - ▶ what kind of jobs they apply for

- ▶ **Approach:** OLS regression at individual i and month t

$$Y_{it} = \alpha + \beta_1 1[\textit{Developed}] + \beta_2 1[\textit{Developing}] + X_i \delta + X_t \gamma + \varepsilon_{ij}$$

- ▶ Specification 0: Raw gap, no controls
 - ▶ Specification 1: $X_i = \{\text{gender, age, education level and field, nb months since spell started, age, 6,000 "neighborhoods" of residence}\}$, $X_t = \text{year-month of app}$
 - ▶ Specification 2: Spec 1 + 4-digit reference occupation (declared at registration)
- ▶ **Sample:** Worker-month (i, t) when i is unemployed.
 - ▶ clicks/apps: 1,426,003 worker-months for 325,499 workers
 - ▶ charac. of apps: 1,385,750 worker-months for 320,353 workers.

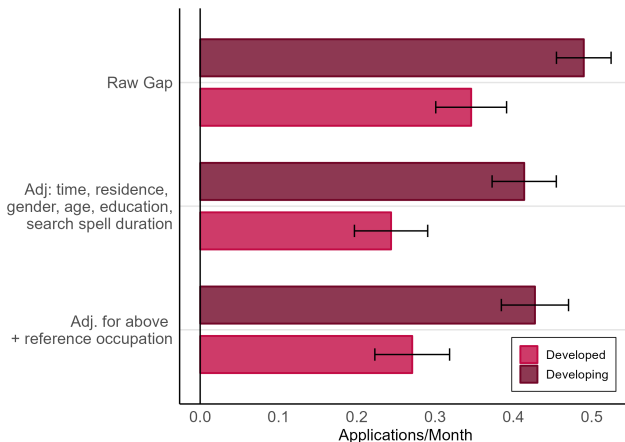
Unemployment duration gap



Note. Average unemployment duration for natives: 9.5 months

- Is it only about differences in search or probability to be hired?

Unemployment duration gap - Search intensity



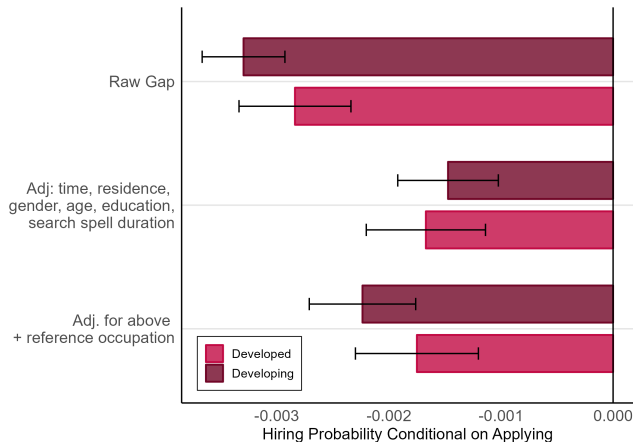
Note. Average No applications/month: 2.4

By time since arrival

No Views

- Differentials in unemployment duration unlikely to be due to diff in job search intensity

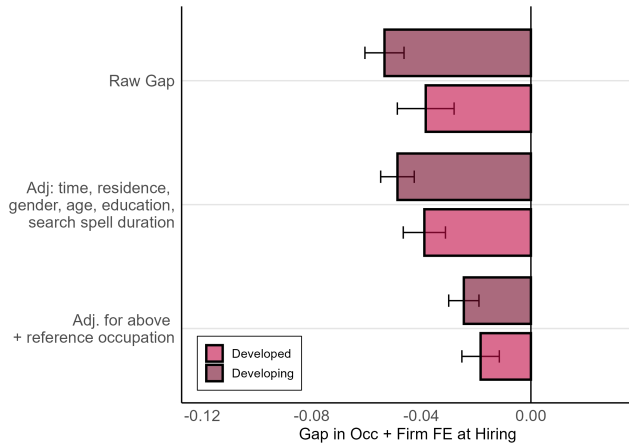
Unemployment duration gap - Hiring probability



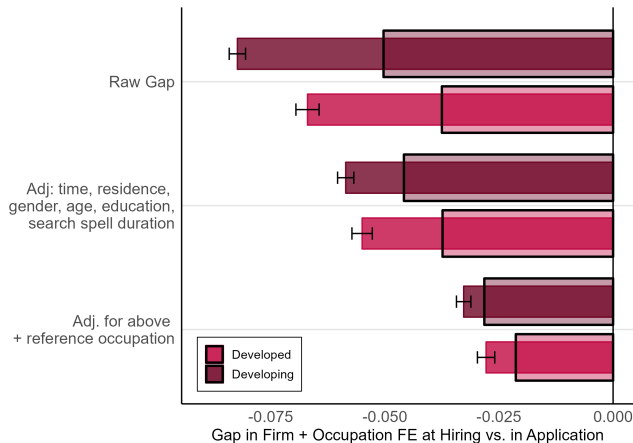
Note. Average hiring probability: 0.012

- Large differences in hiring probabilities. Do migrants apply to jobs that are too highly paid? Or too little?

Earnings Gap - Hiring

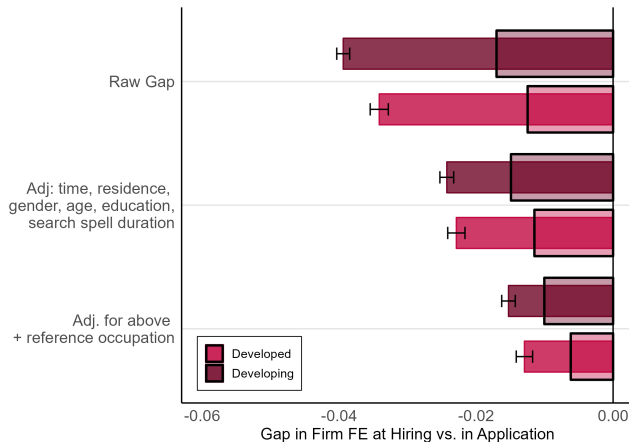


Earnings Gap - Hiring vs Application

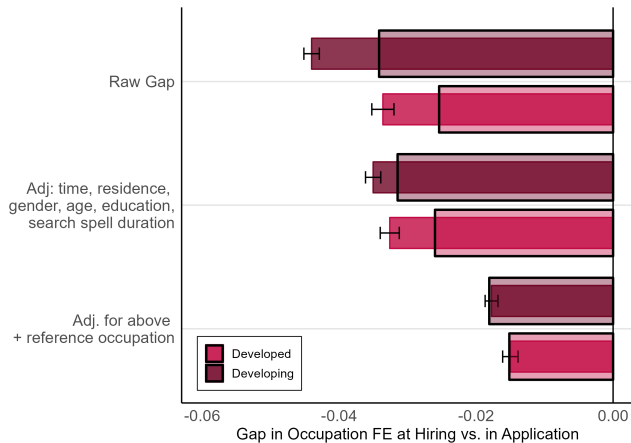


- Large gap in applications, even larger than gap in hiring. Undershooting?

Earnings Gap - Hiring vs Application, Firm



Earnings Gap - Hiring vs Application, Occupation



Other differential in applications

Migrants apply...

- ▶ to jobs that are significantly **further away from home**
 - ▶ Spec0: $-5\%^{***}$ (developed) $+4\%^{***}$ (developing)
 - ▶ Spec2: $+6\%^{***}$ (developed) $+20\%^{***}$ (developing)
- ▶ to firms with a **larger share of migrant employees**
 - ▶ Spec0: $+34\%^{***}$ (developed) $+40\%^{***}$ (developing)
 - ▶ Spec2: $+17\%^{***}$ (developed) $+19\%^{***}$ (developing)
- ▶ significantly **less to open-ended contracts**
 - ▶ Spec0: $-0.5\%^{***}$ (developed) $-2\%^{***}$ (developing)
 - ▶ Spec2: $-0.4\%^{***}$ (developed) $1\%^{***}$ (developing)
- ▶ significantly **less to full-time contracts**
 - ▶ Spec0: $-5\%^{***}$ (developed) $-8\%^{***}$ (developing)
 - ▶ Spec2: $-2\%^{***}$ (developed) $-3\%^{***}$ (developing)

Take-aways

► **Selected Stylized facts:**

Fact 1: Migrants apply more intensively but have lower hiring probability

Fact 2: Migrants apply to firms and occupations that pay less

Fact 3: The earnings gap is larger in applications than in hiring

► **Could job search affect migrant-native gaps?**

- Are differentials in job search rational reactions to differentials in hiring probabilities?
- Or is the hiring probability and earnings gap reflecting a sub-optimal search of migrants compared to natives?

Take-aways

► **Selected Stylized facts:**

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Differences in re-employment outcomes and job search

Application model

Experimental evidence from job recommendations

Application model

- ▶ Assume job seeker i applies to all jobs j such that $p_{ij}w_j > \underline{v}_i$
 - p_{ij} probability i gets job j (conditional on applying)
 - w_j wage of job j for worker i
 - $\underline{v}_i$ the cost of applying
- ▶ Undershoot (information story):
 - if workers under-estimated p_{ij} for high-wage jobs (or over-estimated p_{ij} for low-wage jobs), they would apply for jobs that are paying less than those they should optimally apply for
- ▶ Suggestive empirical test
 - Estimate probability to be hired conditional on applying $p(w_j; m_i)$
 - Assuming rational expectations, compute $w_j \hat{p}(w_j; m_i)$ and compare to actual applications
 - Simplifying assumption: v_i does not depend on j

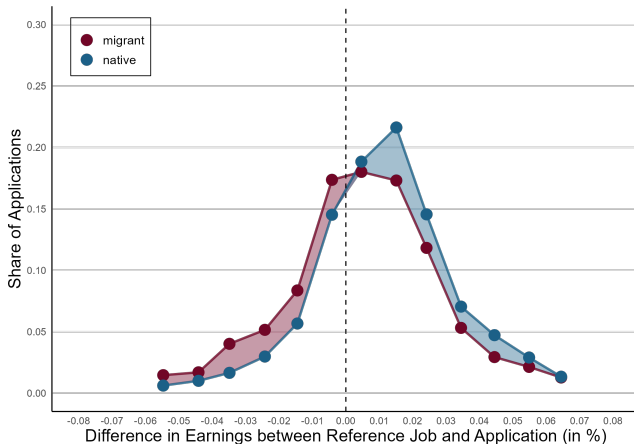
Estimation of $p(w_j; m_i)$

- ▶ Separate job seekers i by reference occupation earnings quintile q_i and migrant status m_i
- ▶ For each cell, we estimate $\hat{p}(\cdot; q_i, m_i)$ using a logit model on all applications:

$$H_{(i,j)} = \sum_{k=1}^{10} \beta_k^{q,m} \cdot \mathbf{1}(W_j \in \text{decile}_k) + X'_{(i,j)} \beta^{q,m} + \varepsilon_{(i,j)}, \quad (1)$$

- $H_{(i,j)} = 1$ iff application (i,j) has led to i being hired in j
 - $\log(W_j)$: log earnings potential of the vacancy, grouped by decile k
 - $X_{(i,j)}$ distance to the vacancy, unemp duration, nb of positions advertised, year FE
- ▶ Using the estimated function $\hat{p}(\cdot; q_i, m_i)$, we can compute:
 $\hat{p}(w; q_i, m_i)$ and $w\hat{p}(w; q_i, m_i)$

Do migrants undershoot?



Sample: 1st quintile of log-earnings in reference occupation

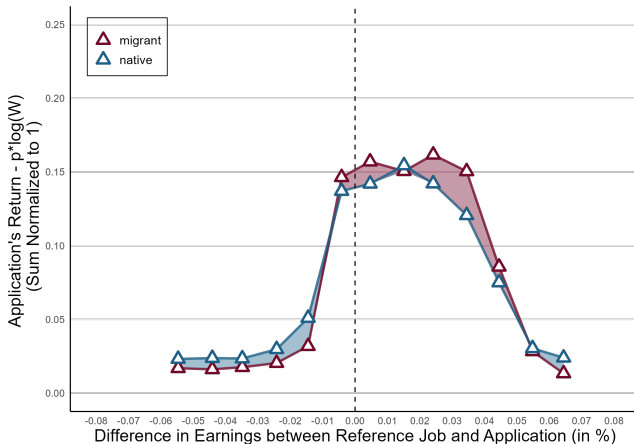
Q2

Q3

Q4

Q5

Do migrants undershoot? Looks like they do.



Sample: 1st quintile of log-earnings in reference occupation

Q2

Q3

Q4

Q5

Take-away on under-shooting

► Stylized facts:

Fact 1: At the bottom of the income distribution, migrants over-apply to low-paying jobs relative to natives

Fact 2: At the top of the income distribution, the difference in applications might be rationalized by differences in returns

► **Open question:** Would migrants be better off if they shot higher?

- Outcome: How would p_{ij} change if the pool of applications changed?
- Ideal setting: an experiment where migrants and natives exogenously apply to lower/high-paying jobs

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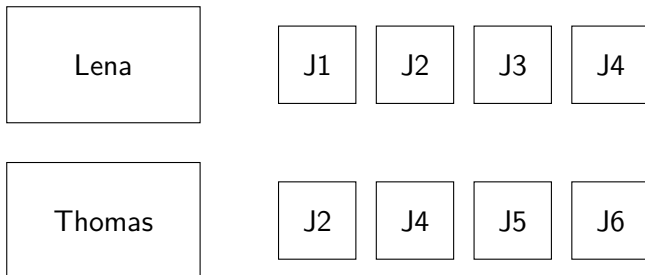
Experimental evidence from job recommendations

Experimental Design (Le Barbanchon et al., 2023)

- ▶ Population: around 250,000 registered unemployed job seekers.
- ▶ Algorithm: generate recommendations to job seekers ($\approx$ 10/day) , based on the past click history (April 2021 - March 2022). [Details](#)
- ▶ Two-sided randomization:
 - ▶ Job seekers permanently assigned to treatment or control.
 - ▶ Job ads also permanently assigned to treatment or control.
- ▶ Why this experiment is useful for us:
 - ▶ random assignment of vacancies to treated (vs. control) induces **random variation in the job's earnings** they are exposed to.
 - ▶ generates **exogenous shift**: some job seekers are nudged to apply to higher- or lower-paying jobs.

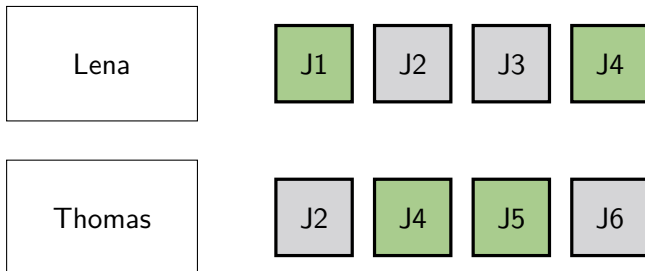
Experimental Design - Example

- Example: 2 jobs seekers, with recommended jobs J .



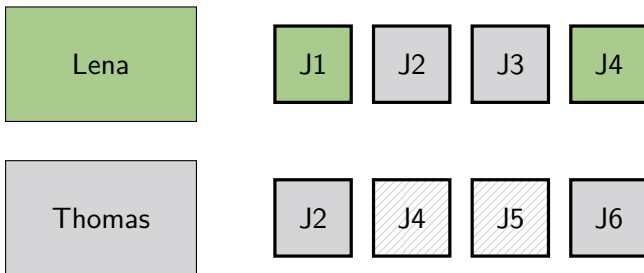
Experimental Design - Example

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



Experimental Design - Example

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



Recommendations in practice

Where is the workplace?

📍 Master Samuelsgatan 46A
10638 Stockholm

The employer

H & M Hennes & Mauritz Gbc AB

Share the ad

@ Email Facebook Twitter LinkedIn Print the ad

Ad Id: 24717788

Published: April 19, 2021, at 13.03

Apply by **April 29** (in 10 days)

Enter the reference **Senior Business Controller** in your application

@ Apply by email

Email your application to
ida.lundwall@hm.com

Suggestions for you

Environmental and health protection...

Ekerö municipality - Ekerö

Environmental protection officer for...

Swedish Environmental Protection Agency - Stockholm

Environmental strategist for energy...

Jefferson Wells - Stockholm

Quality and environmental...

Nyckelrekrytering AB - Stockholm

Sustainability developer for...

Fastighets AB Förvaltaren - Sundbyberg

Show all ^

The “being showed jobs that lead to employment” treatment

- ▶ **Question:** Can we use this RCT to study undershooting?
- ▶ **Methodology:** Use randomness of vacancy assignment to treatment within recommended job set
 - High binary treatment: Treated vacancies have a higher predicted hiring probability than control vacancies
 - Regression: For treated job seekers, regress outcome measured for worker i on day d on *High* treatment (with or without worker FE):

$$Y_{i,d} = \alpha + \textit{High}_{i,d} + \varepsilon_{i,d}$$

$$Y_{i,d} = \alpha_i + \textit{High}_{i,d} + \varepsilon_{i,d}$$

- Outcome of interest: Probability to be hired in recommended jobs

Number of applications

	N apps			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	0.1723*** (0.0016)		0.1313*** (0.0012)	
High=1	0.0017 (0.0022)	0.0002 (0.0023)	0.0006 (0.0016)	0.0009 (0.0017)
Indiv FE		✓		✓
Observations	180,492	172,169	237,490	224,726

control

Predicted hiring probability (applications)

	Hiring Probability			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	0.0076*** (0.0001)		0.0099*** (0.0001)	
High=1	0.0008*** (0.0001)	0.0006*** (0.0001)	0.0006*** (0.0001)	0.0002* (0.0001)
Indiv FE		✓		✓
Observations	33,320	26,235	35,275	25,018

control

Predicted log-earnings (applications)

	Application FE			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	10.3444*** (0.0019)		10.4308*** (0.0018)	
High=1	-0.0021 (0.0027)	0.0002 (0.0025)	-0.0015 (0.0026)	-0.0019 (0.0027)
Indiv FE		✓		✓
Observations	33,320	26,235	35,275	25,018

control

Hiring conditional on applying

	Hiring Probability			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	0.0121*** (0.0009)		0.0165*** (0.0009)	
High=1	0.0017 (0.0012)	0.0023* (0.0013)	-0.0019 (0.0013)	0.0002 (0.0015)
Indiv FE		✓		✓
Observations	33,338	26,248	35,264	25,010

control

“Being showed jobs that lead to employment”: Take-away

- ▶ For migrants:
 - ▶ Recommending jobs where workers have a higher probability to be successful leads them to apply to this kind of jobs
 - ▶ They ultimately are more successful
 - ▶ with no effect on predicted earnings
- ▶ For natives:
 - ▶ not much going on as first stage is weaker
- ▶ Suggests that there could be higher information frictions leading migrants to apply to jobs that lower p for the same w .

The “being showed higher-paid jobs” treatment

- ▶ **Question:** Can we use this RCT to study undershooting?
- ▶ **Methodology:** Use randomness of vacancy assignment to treatment within recommended job set
 - High binary treatment: Treated vacancies are more often better paid than reference occupation than control vacancies
 - Regression: For treated job seekers, regress outcome measured for worker i on day d on *High* treatment (with or without worker FE):

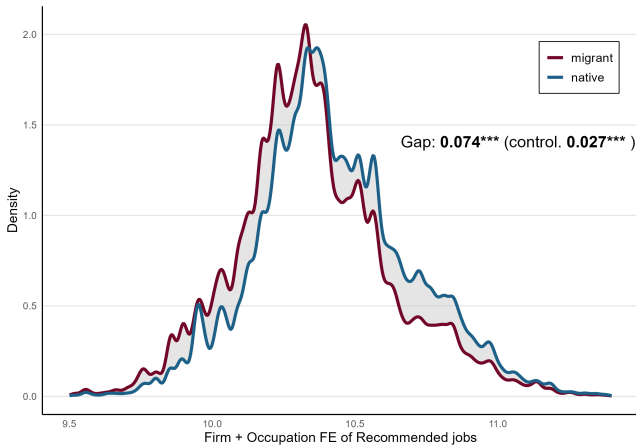
$$Y_{i,d} = \alpha + \textit{High}_{i,d} + \varepsilon_{i,d}$$

$$Y_{i,d} = \alpha_i + \textit{High}_{i,d} + \varepsilon_{i,d}$$

- Outcome of interest: Probability to be hired in recommended jobs
- First-stage: shift in recommended jobs need to shift application earnings

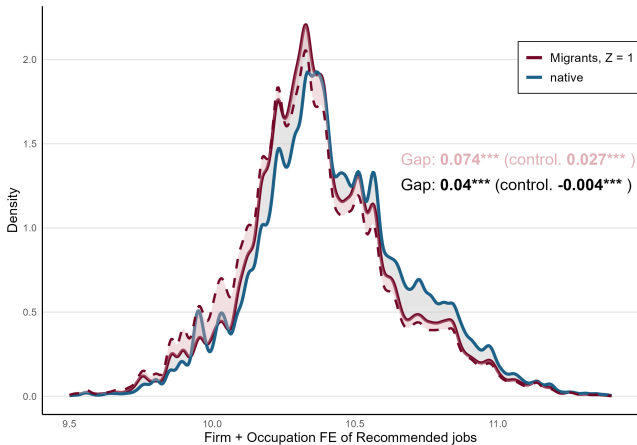
The “being showed higher-paid jobs” treatment

Figure: Distribution earnings of recommended jobs



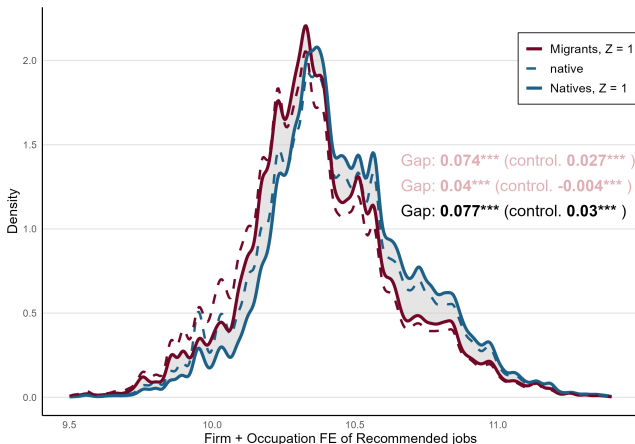
The “being showed higher-paid jobs” treatment

Figure: Distribution earnings of recommended jobs, Migrants pushed



The “being showed higher-paid jobs” treatment

Figure: Distribution earnings of recommended jobs, Migrants and natives pushed



Number of applications

	N apps			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	0.1723*** (0.0016)		0.1314*** (0.0012)	
High=1	0.0017 (0.0022)	0.0006 (0.0023)	0.0004 (0.0016)	0.0007 (0.0017)
Indiv FE		✓		✓
Observations	180,492	172,169	237,490	224,726

control

Predicted log-earnings (applications)

	Application FE			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	10.3124*** (0.0021)		10.4055*** (0.0021)	
High=1	0.0129*** (0.0030)	0.0187*** (0.0030)	0.0088*** (0.0029)	0.0155*** (0.0033)
Indiv FE		✓		✓
Observations	25,807	19,385	27,064	17,983

control

Predicted hiring probability (applications)

	Predicted Hiring Proba			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	0.0080*** (0.0001)		0.0105*** (0.0001)	
High=1	0.0002 (0.0002)	0.0003** (0.0002)	0.0000 (0.0002)	-0.0001 (0.0002)
Indiv FE		✓		✓
Observations	25,807	19,385	27,064	17,983

control

Hiring conditional on applying

	Hiring Proba			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	0.0112*** (0.0010)		0.0166*** (0.0011)	
High=1	0.0015 (0.0014)	-0.0006 (0.0015)	-0.0022 (0.0015)	-0.0020 (0.0017)
Indiv FE		✓		✓
Observations	25,807	19,385	27,064	17,983

control

“Being showed higher-paid jobs”: Take-away

- ▶ For both migrants and natives:
 - ▶ Recommending jobs that pay better leads them to apply to this kind of jobs
 - ▶ The jobs they apply to have a higher (migrants) or similar (natives) predicted hiring probability
 - ▶ There is no impact on the actual hiring probability
- ▶ Pushing workers towards higher-paying jobs do not harm their probability to be hired.

Conclusions

- ▶ Descriptive evidence
 - Migrants search more intensively, and apply to lower quality jobs than natives
 - They have lower probability to be hired and lower earnings when hired
 - Migrants who apply to the same kind of jobs as natives get similar earnings and shorter unemployment duration
- ▶ Is it undershooting, or simply consistent with rational expectations on probabilities to be hired?
 - Suggestive evidence: Migrants do seem to undershoot at the bottom of income distribution
- ▶ Use recommender system to study whether pushing migrants to better jobs could make them better off:
 - Evidence for some information frictions, and room for intervention to bridge earnings gap.

THANK YOU!

SUPPLEMENT SLIDES

Earnings fixed effects

► Occupation earnings fixed effects:

- Data: use yearly wage data that surveyed 50% of firms (2015-2019)
- Regression on workers i , year t :

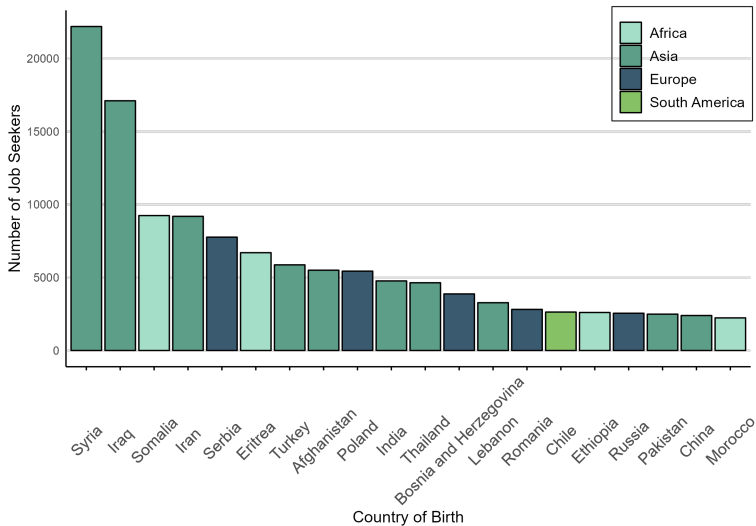
$$\text{LogEarnings}_{i,t} = \beta_1 \text{gender}_i + \beta_2 \text{age}_{i,t} + \beta_3 \text{origin}_i + \beta_4 \text{FirmFE} + \gamma \text{occ}_{i,t} + \varepsilon_{i,t}$$

► Firm earnings fixed effects:

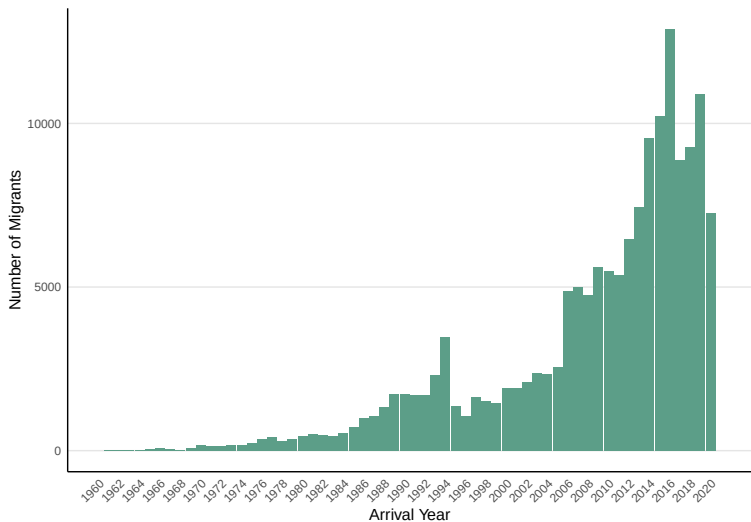
- Data: from employment registers, on unemployed workers past experience, but no information on occupation (2015-2019)
- Regression on workers i , year t :

$$\text{LogEarnings}_{i,t} = \beta_1 \text{gender}_{i,t} + \beta_2 \text{age}_{i,t} + \beta_3 \text{origin}_i + \beta_4 \text{education}_{i,t} + \beta_5 \text{zipcode}_{i,t} + \gamma \text{FirmFE} + \varepsilon_{i,t}$$

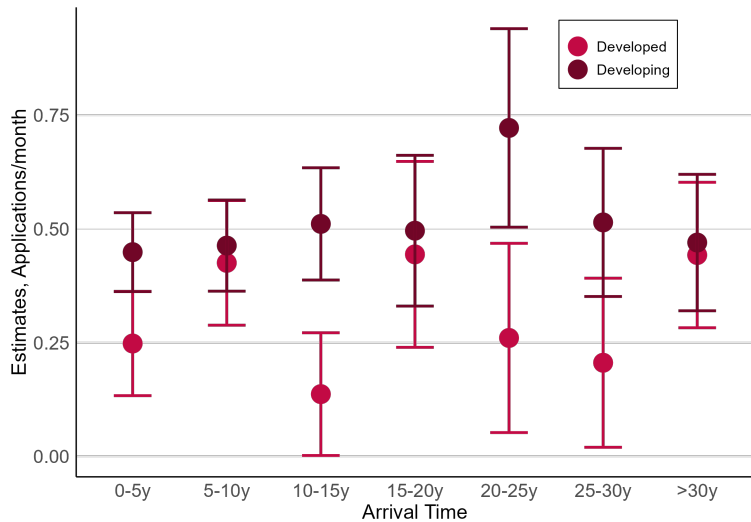
Countries of Origin



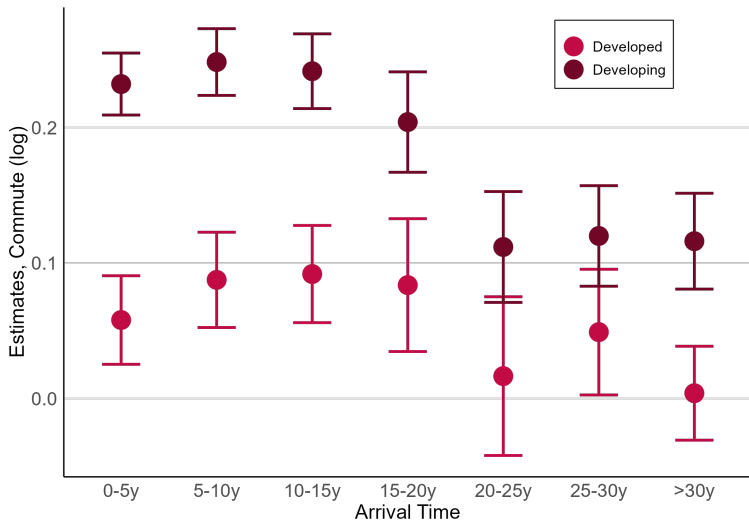
Year since migration



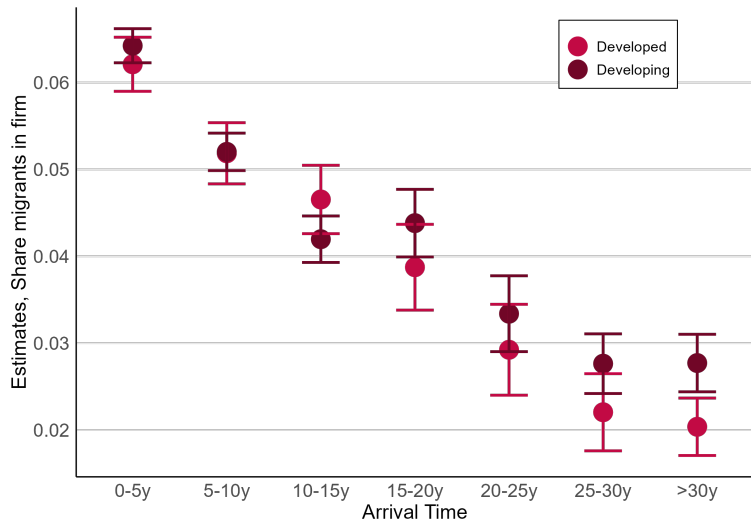
App/Month gap-by time since arrival



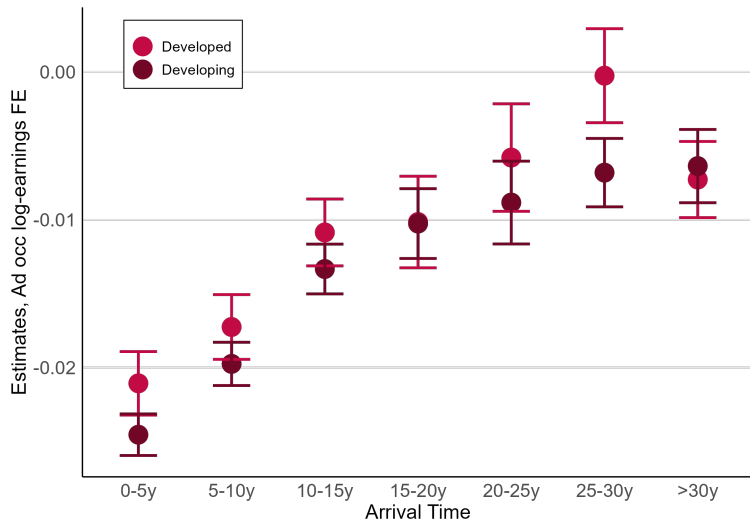
Commuting gap-by time since arrival



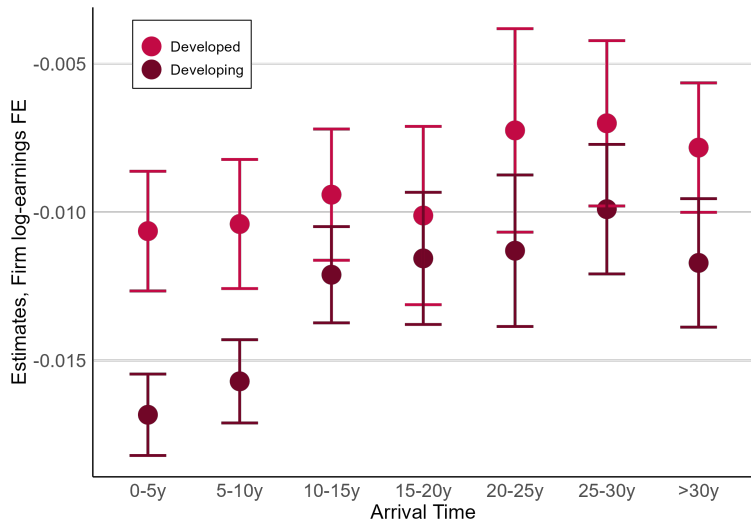
Share Migrants-by time since arrival



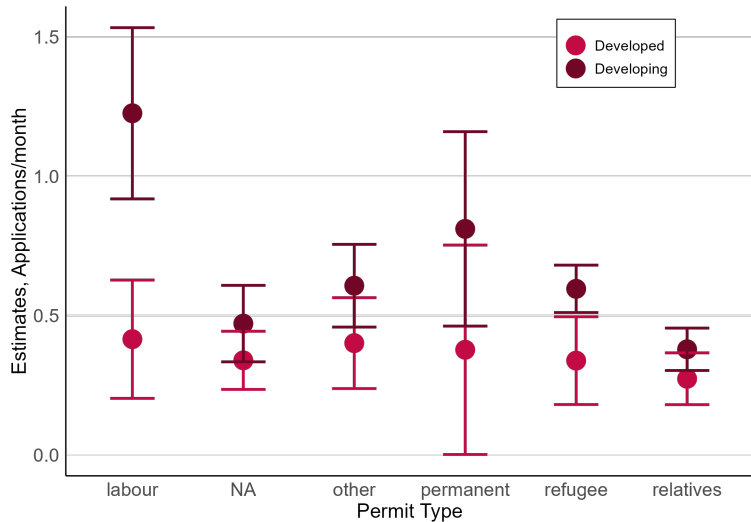
Occupational earnings-by time since arrival



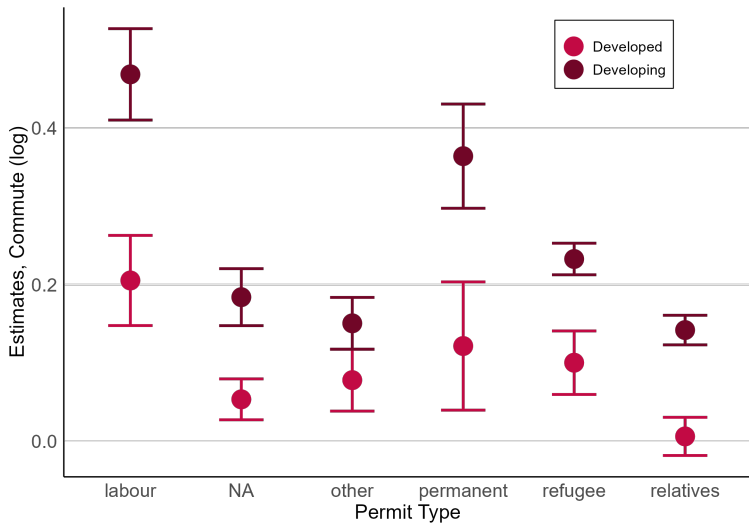
Employer earnings-by time since arrival



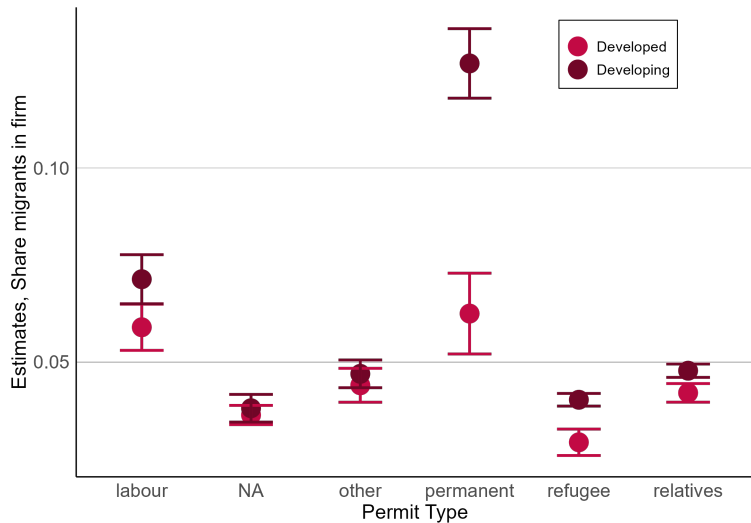
App/Month gap-by residency permit type



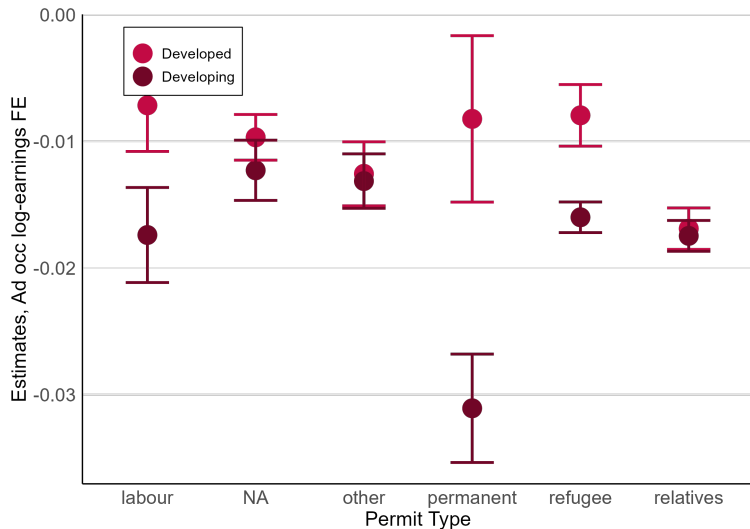
Commuting gap-by residency permit type



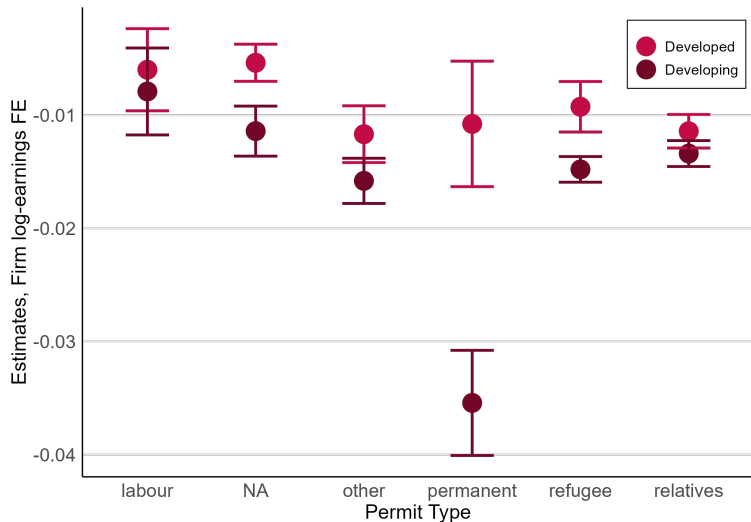
Share Migrants-by residency permit type



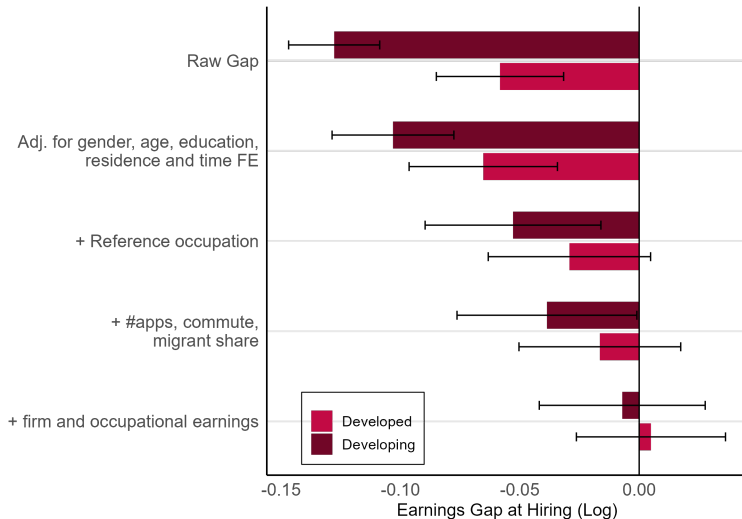
Occupational earnings-by residency permit type



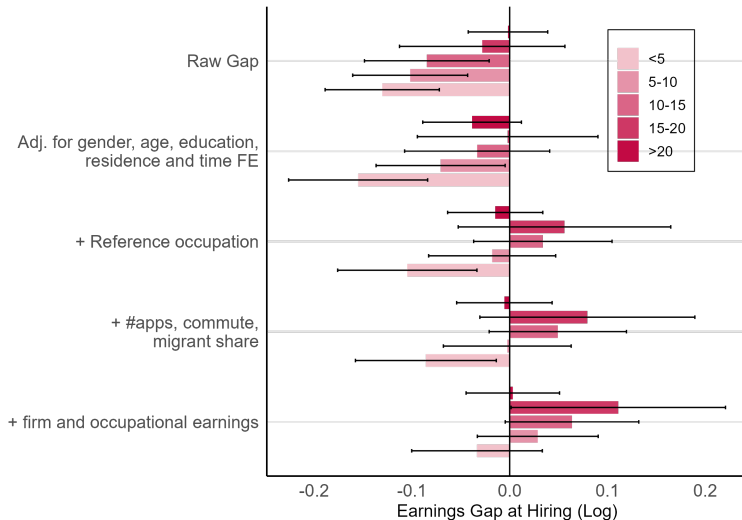
Employer earnings-by residency permit type



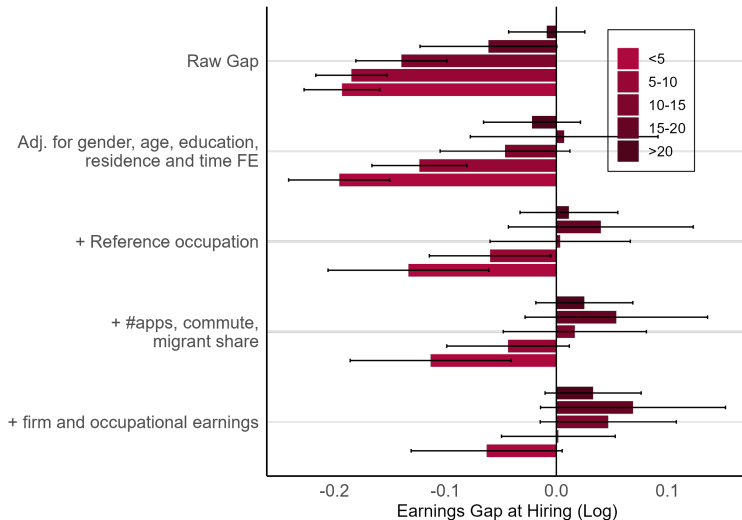
Can differences in job search explain earnings gap?



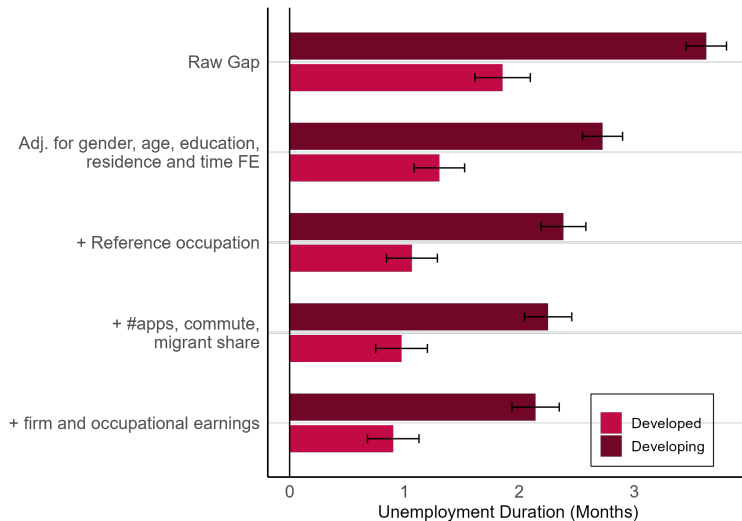
Can differences in job search explain earnings gap? Time since arrival - Developed



Can differences in job search explain earnings gap? Time since arrival - Developing



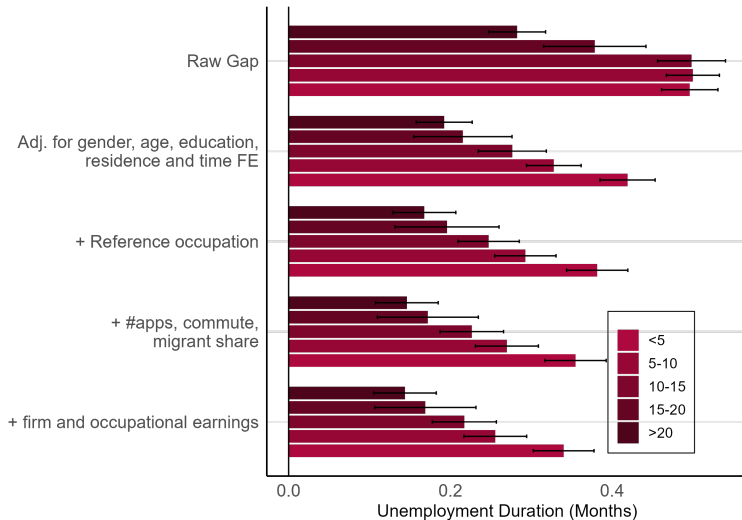
Can differences in job search explain unemployment duration?



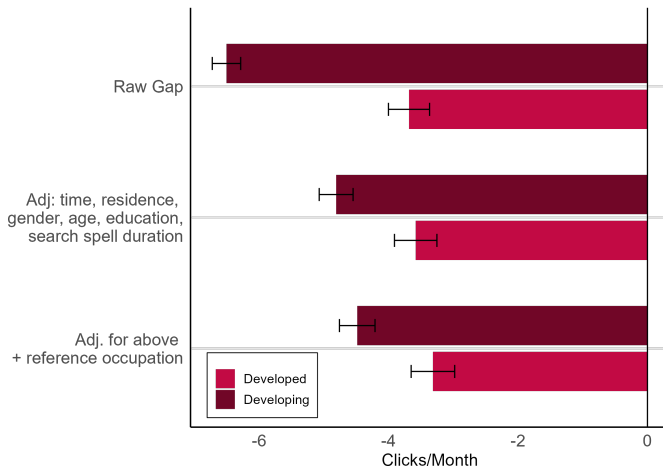
Can differences in job search explain unemployment duration? Time since arrival - Developed



Can differences in job search explain unemployment duration? Time since arrival - Developing



Migrant-native differentials in applications: Job ad views per month



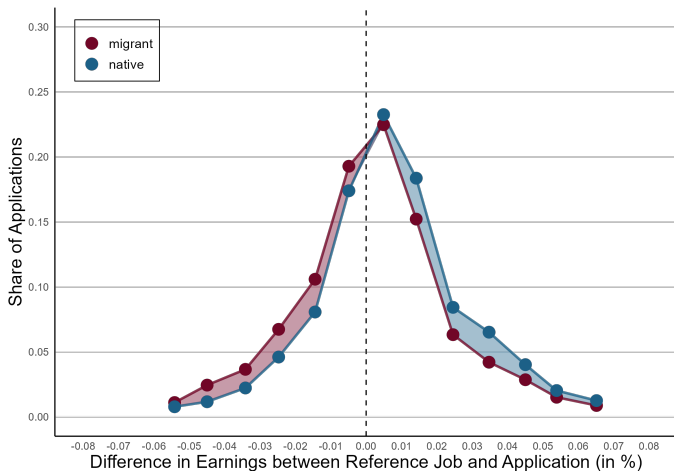
► Native average: 22.2 [Back](#)

Estimation of $p(w_j; m_i)$: Sample

- ▶ Nb app (sample size): 6,812,792
- ▶ Nb workers: 317,681
- ▶ Nb jobs: 837,122
- ▶ Nb employers: 36,285
- ▶ Nb hires: 56,269

Back

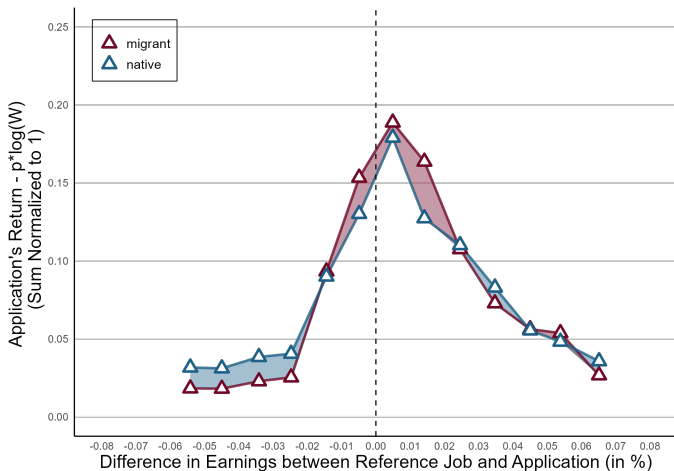
Do Migrants Undershoot? Share of Applications



Sample: 2nd quintile of log-earnings in reference occupation

Back

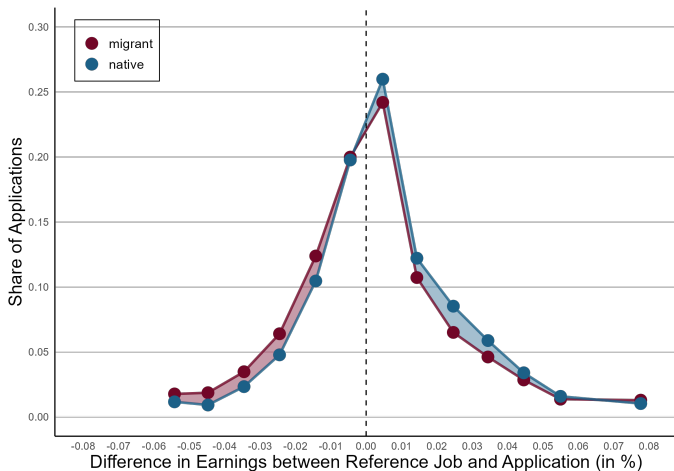
Do Migrants Undershoot? Application's Return



Sample: 2nd quintile of log-earnings in reference occupation

[Back](#)

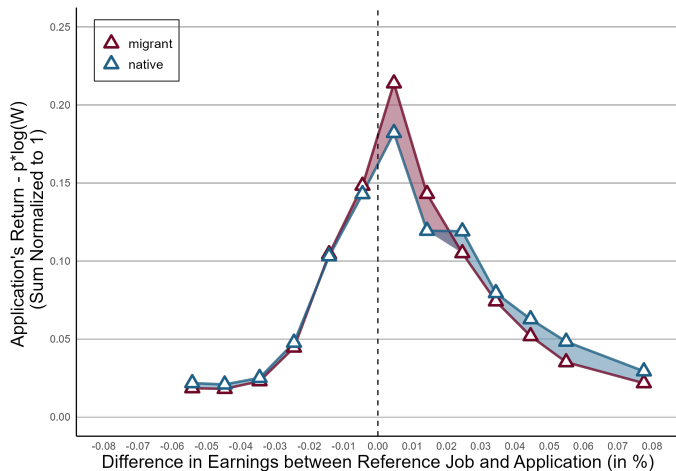
Do Migrants Undershoot? Share of Applications



Sample: 3rd quintile of log-earnings in reference occupation

Back

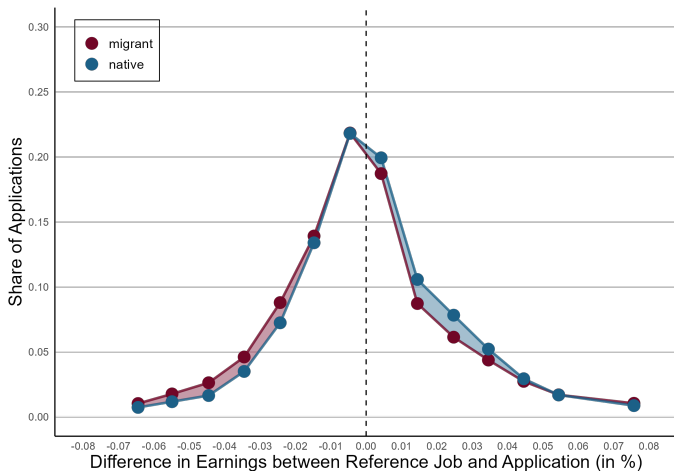
Do Migrants Undershoot? Application's Return



Sample: 3rd quintile of log-earnings in reference occupation

Back

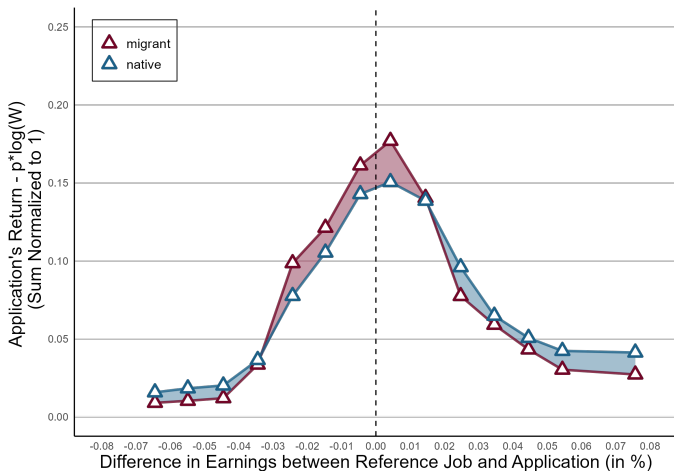
Do Migrants Undershoot? Share of Applications



Sample: 4th quintile of log-earnings in reference occupation

Back

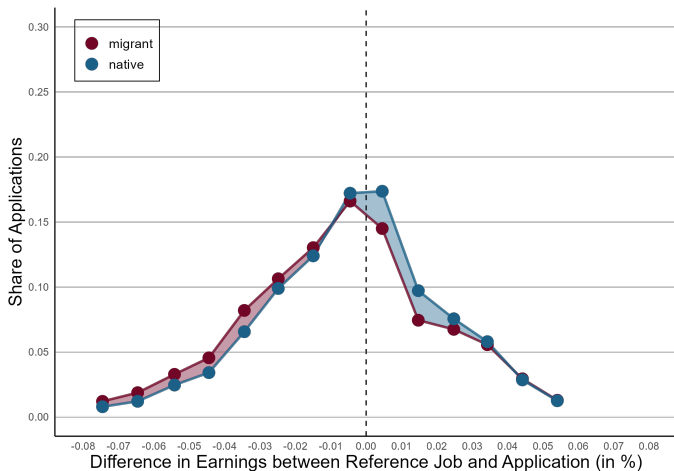
Do Migrants Undershoot? Application's Return



Sample: 4th quintile of log-earnings in reference occupation

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Do Migrants Undershoot? Share of Applications



Sample: 5th quintile of log-earnings in reference occupation

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Do Migrants Undershoot? Application's Return



Sample: 5th quintile of log-earnings in reference occupation

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Number of applications - Control

	N apps			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	0.1383*** (0.0014)		0.1181*** (0.0011)	
High=1	0.0052*** (0.0020)	0.0032 (0.0021)	-0.0021 (0.0015)	-0.0018 (0.0016)
Indiv FE		✓		✓
Observations	180,833	172,365	240,898	228,252

[Back](#)

First stage - Predicted Hiring probability of applications - Control

	Predicted Hiring Probability			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	0.0089*** (0.0001)		0.0106*** (0.0001)	
High=1	-0.0005*** (0.0001)	-0.0005*** (0.0002)	0.0001 (0.0001)	0.0000 (0.0001)
Indiv FE		✓		✓
Observations	27,618	20,969	32,279	22,363

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First stage - Earning FE of applications - Control

	Application FE			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	10.3459*** (0.0021)		10.4324*** (0.0019)	
High=1	-0.0033 (0.0030)	-0.0032 (0.0027)	-0.0018 (0.0026)	-0.0023 (0.0027)
Indiv FE		✓		✓
Observations	27,618	20,969	32,279	22,363

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Hiring Probability conditional on applying - Control

	Hiring Probability			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	0.0156*** (0.0010)		0.0172*** (0.0010)	
High=1	-0.0022 (0.0014)	-0.0030* (0.0016)	0.0003 (0.0015)	-0.0002 (0.0017)
Indiv FE		✓		✓
Observations	27,645	20,993	32,253	22,339

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Number of applications - Control

	mean_fe_qual_app			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	0.1407*** (0.0014)		0.1174*** (0.0011)	
High=1	0.0003 (0.0020)	0.0001 (0.0021)	-0.0007 (0.0015)	0.0006 (0.0016)
Indiv FE		✓		✓
Observations	180,833	172,365	240,898	228,252

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First stage - Earning FE of applications - Control

	Application FE			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	10.3171*** (0.0024)		10.4082*** (0.0021)	
High=1	0.0067** (0.0033)	0.0030 (0.0034)	0.0066** (0.0030)	0.0050 (0.0034)
Indiv FE		✓		✓
Observations	21,312	15,284	24,643	15,837

[Back](#)

First stage - Predicting Hiring Probability of applications - Control

	Predicted Hiring Proba			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	0.0086*** (0.0001)		0.0109*** (0.0001)	
High=1	0.0000 (0.0002)	-0.0000 (0.0002)	-0.0003 (0.0002)	-0.0002 (0.0002)
Indiv FE		✓		✓
Observations	21,312	15,284	24,643	15,837

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Hiring probability conditional on applying - Control

	Hiring Proba			
	Migrants		Natives	
	(1)	(2)	(1)	(2)
Intercept	0.0133*** (0.0011)		0.0193*** (0.0012)	
High=1	0.0015 (0.0016)	-0.0017 (0.0019)	-0.0030* (0.0017)	-0.0052** (0.0021)
Indiv FE		✓		✓
Observations	21,312	15,284	24,643	15,837

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Decomposition of migrant-native gaps

- ▶ **Aim:** Assess the gap in earnings and unemployment duration due to diff. in demographics and job search behaviour.
- ▶ **Approach:** OLS regressions:

$$Y_i = \alpha + \beta_1 1[Developed] + \beta_2 1[Developing] + X_i \delta + \varepsilon_i$$

- ▶ *Spe 1:* Raw gap, no controls
- ▶ *Spe 2:* Demographic characteristics: $X_i = \{\text{age, gender, education level and field}\}$
- ▶ *Spe 3:* Spec 2 + Occupation declared as searched (4-dig, 404 occ.)
- ▶ *Spe 4:* Spec 3 + monthly average: number of applications, average distance b/w distance of the vac applied to and residence, and share of migrants in the vac applied to.
- ▶ *Spe 5:* Spec 4 + monthly average of occupation earnings FE and firm earnings FE of the vacancies applied to

Earnings gap

Log-earnings at hiring					
	Spe 1	Spe 2	Spe 3	Spe 4	Spe 5
Developed	−0.053 (0.012)	−0.05 (0.012)	−0.014 (0.014)	−0.001 (0.014)	0.017 (0.013)
Developing	−0.128 (0.009)	−0.11 (0.010)	−0.046 (0.02)	−0.02 (0.020)	0.012 (0.018)
Native mean	SEK 17,327				
Nb Obs	40,824	40,824	40,598	40,574	40,563

Unemployment duration gap

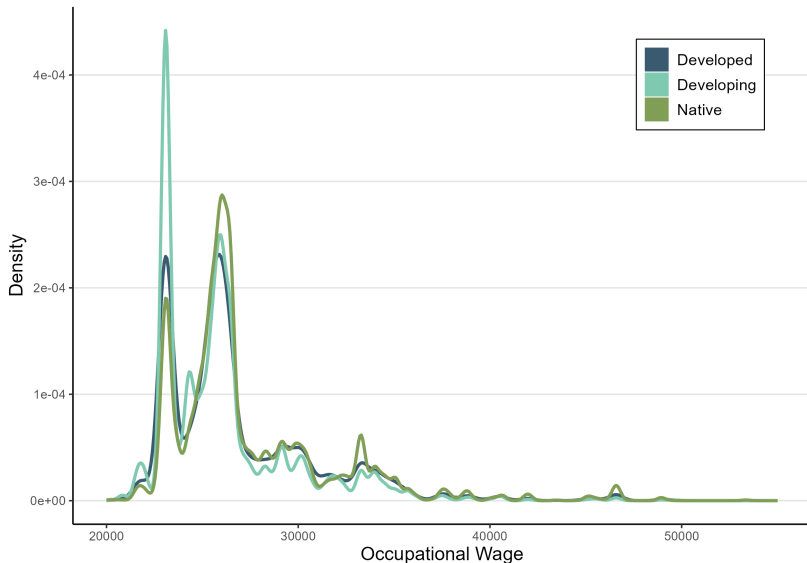
Unemployment duration (months)					
	Spe 1	Spe 2	Spe 3	Spe 4	Spe 5
Developed	2.26 (0.14)	2.08 (0.14)	1.78 (0.19)	1.47 (0.17)	1.36 (0.17)
Developing	5.00 (0.11)	4.97 (0.11)	4.30 (0.16)	3.63 (0.16)	3.45 (0.16)
Native mean	11.5 months				
Nb Obs	40,824	40,824	40,598	40,574	40,563

Experimental Design - Algorithm

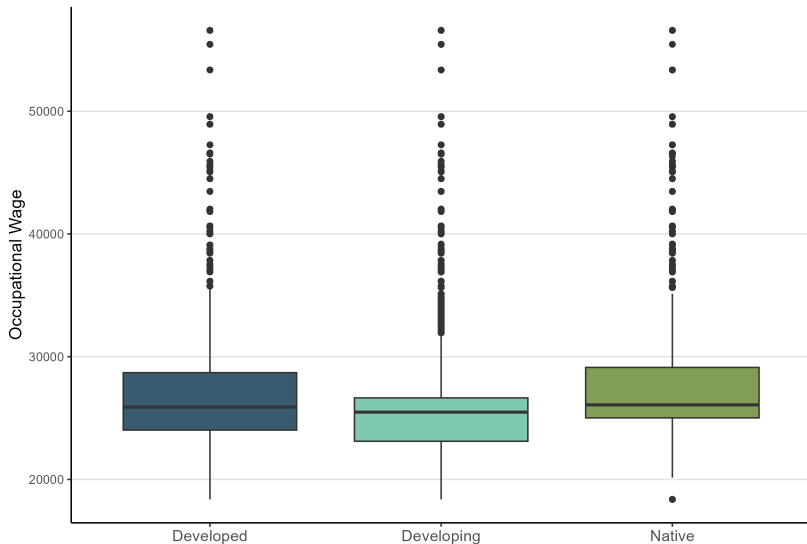
- ▶ Item-to-user collaborative-filtering recommender system with implicit feedback
- ▶ When users click on vacancies, they *implicitly* rate them
- ▶ Input: 30 days of past click history
 - ▶ “naturally occurring” data on such websites
- ▶ Intermediate parameters: unobserved types of each vacancy and 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

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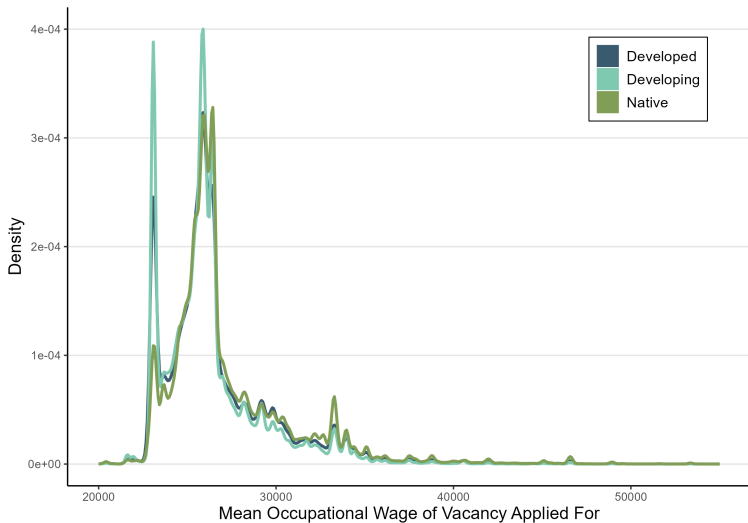
Occupation wage: declared occupation (monthly, SEK)



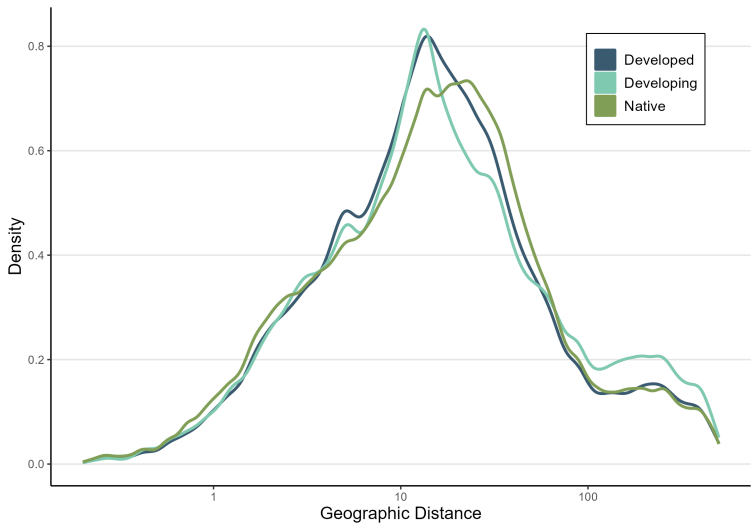
Occupation wage: declared occupation (monthly, SEK)



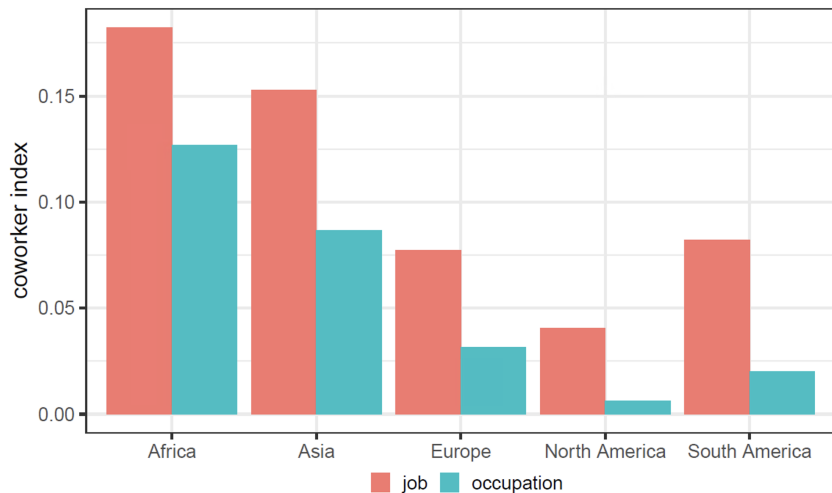
Occupational wage: applications (monthly, SEK)



Commute: applications (km)



Are all groups similarly segregated?

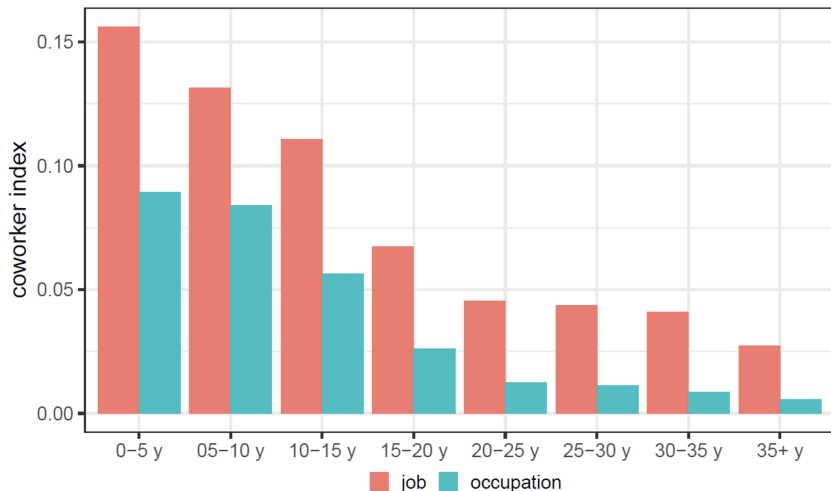


- ▶ Index corrected à la D'Haultfoeuille and Rathelot (2017)
- ▶ job level vs. occupation level

The D'Haultfoeuille and Rathelot (2017) correction

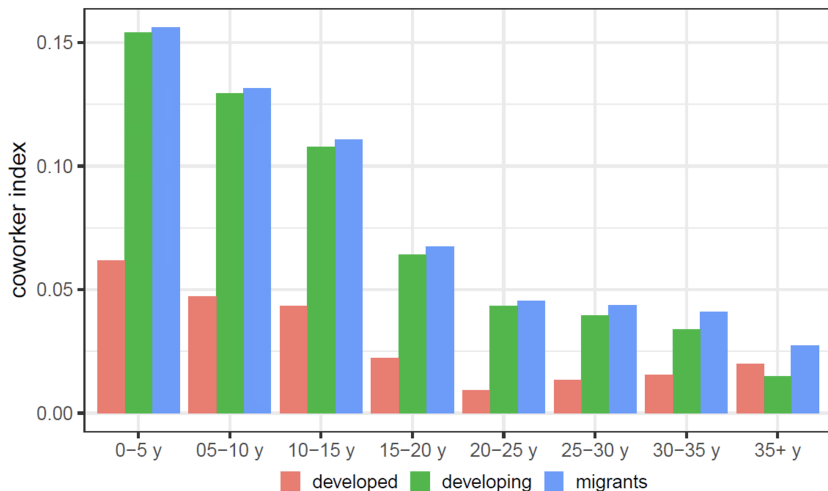
- ▶ Useful to debias segregation indices when units are small
- ▶ Jobs may differ in terms of underlying probability for migrants to apply p_j (underlying distribution F_p)
- ▶ Observed share of migrants M_j/K_j is such that $M_j \sim \mathcal{B}(K_j, p_j)$
 - ▶ If we use observed shares of migrants to compute segregation, result is biased upwards: naive estimator pools true segregation and sampling error
- ▶ True coworker index: $\frac{\text{Var}(p)}{E(p)(1-E(p))}$
- ▶ Th. 1 in DHR: if size of units is K , the first K moments of F_p are point identified

Is segregation diminishing with time spent in Sweden?



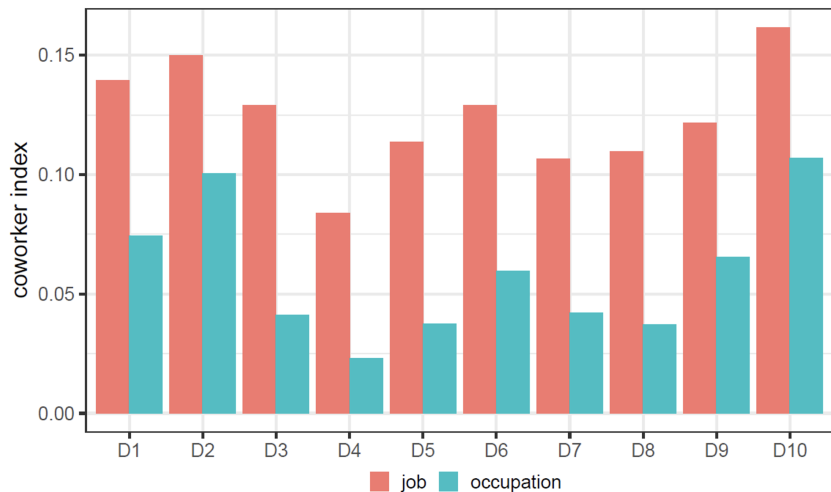
- ▶ Index corrected à la D'Haultfoeuille and Rathelot (2017)
- ▶ job level vs. occupation level

Is segregation diminishing with time spent in Sweden?



- ▶ Index corrected à la D'Haultfoeuille and Rathelot (2017)
- ▶ job level

Do better paid jobs exhibit less segregation in apps?



- ▶ Index corrected à la D'Haultfoeuille and Rathelot (2017)
- ▶ job level vs. occupation level

Estimation of the probability to be hired

- ▶ We split job seekers i into cells by initial occupation declared as searched (5 groups) and migrant status (s_i, m_i)
- ▶ For each cell, we estimate $\hat{p}(\cdot; s_i, m_i)$ using within-individual conditional logit on all applications (i, j) :

$$H_{(i,j)} = \sum_{k=1}^{10} \beta_k \cdot 1(\log(W_j) \in \text{decile}_k) + X'_{(i,j)}\beta + \lambda_i + \varepsilon_{(i,j)}$$

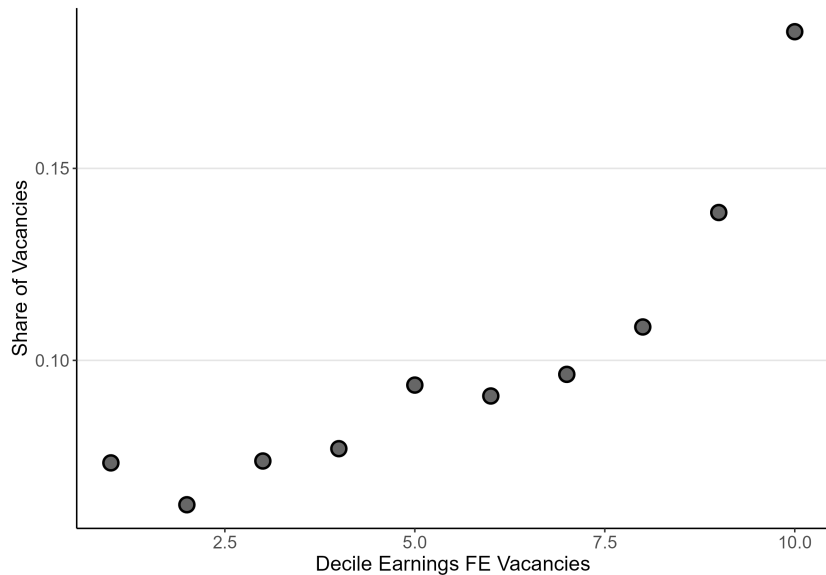
- $H_{(i,j)} = 1$ iff application (i, j) has led to i being hired in j
 - $\log(W_j)$: log earnings of the vacancy (empirically proxied by the sum of the occupational and firms' earnings FE), grouped by decile k
 - $X_{(i,j)}$ contains the distance to the vacancy, unemp duration, nb of positions advertised, year FE
- ▶ Using the estimated function $\hat{p}(\cdot; s_i, m_i)$, we can compute:

$$\hat{p}(w; s_i, m_i) \text{ and } w\hat{p}(w; s_i, m_i)$$

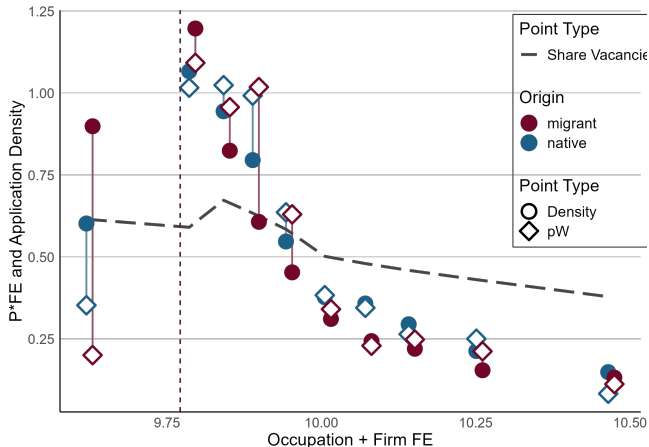
Do migrants undershoot?

- ▶ Remember $A_{ij} = 1(p_{ij} W_{ij} > v_i)$
- ▶ Suppose main job value is wage
- ▶ Suppose similar distribution of available ads for migrants and natives
- ▶ If job ad distribution and v_i uniform, application distribution should be close to expected returns distribution
- ▶ If more complex job ad distribution, similar deviation of apps from returns distribution for migrants and natives

Job ad density



Do migrants undershoot? It looks like it.

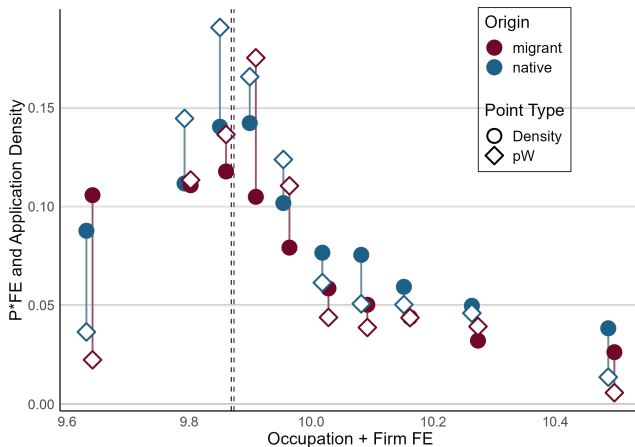


Sample: First quintile of log-earnings declared as searched

- Migrants tend to undershoot

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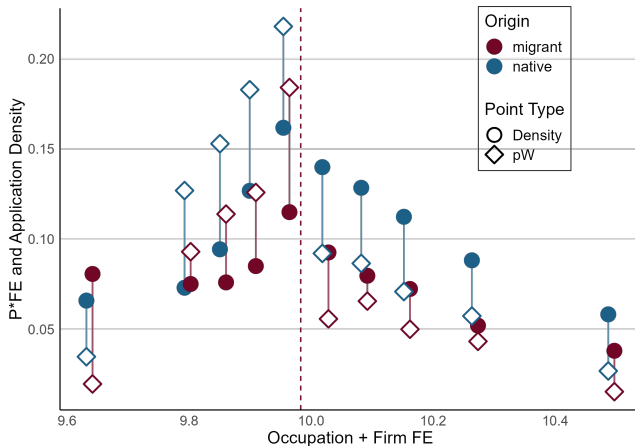
Do migrants undershoot? It looks like it.



Sample: Second quintile of log-earnings declared as searched

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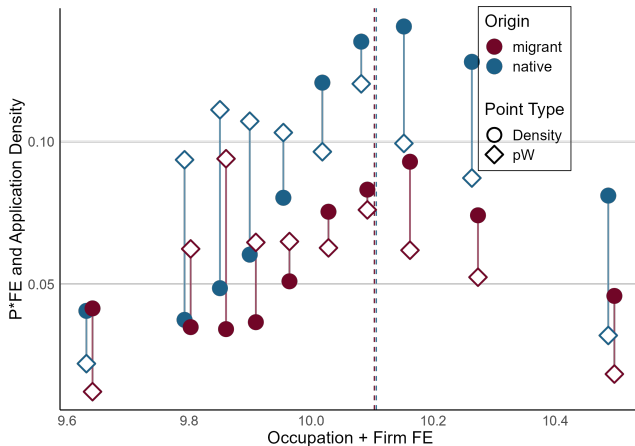
Do migrants undershoot? It looks like it.



Sample: Third quintile of log-earnings declared as searched

[Back](#)

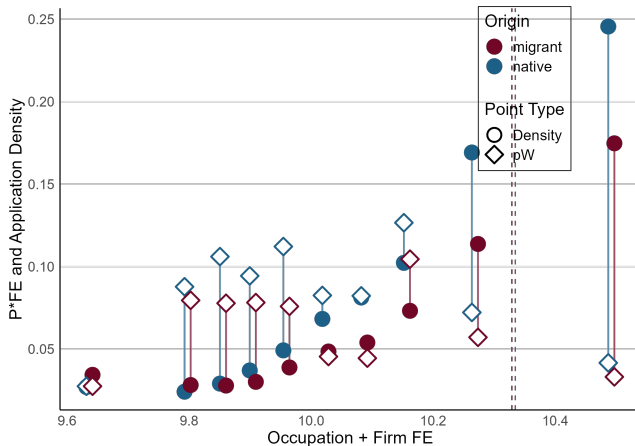
Do migrants undershoot? It looks like it.



Sample: Fourth quintile of log-earnings declared as searched

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Do migrants undershoot? It looks like it.

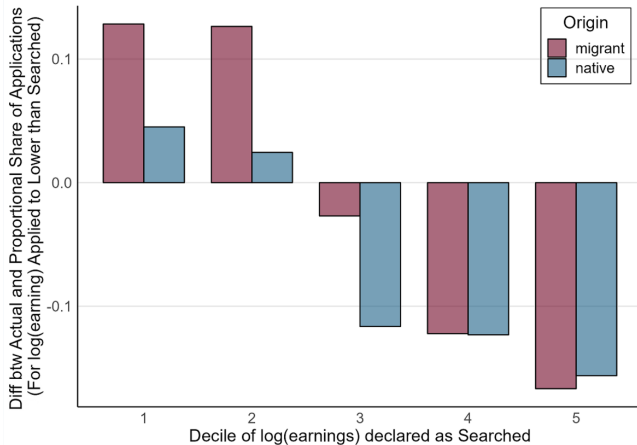


Sample: Fifth quintile of log-earnings declared as searched

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Predicted Hiring Probability VS Application Share

Figure: First quintile of log-earnings declared as searched



Treatment effect on number of applications

Sample: (i, d) such that unemployed job seeker i view at least one ad on day d , aggregated at the individual day level

	Number of daily applications made towards			
	All jobs	Recommended jobs		
		Yes	Yes but not shown (Control jobs)	No
Swedish	-0.29*** (0.001)	-0.01*** (0.0002)	-0.01*** (0.0002)	-0.26*** (0.001)
Treated	-0.013*** (0.001)	0.012*** (0.0002)	-0.0008*** (0.0003)	-0.024*** (0.002)
Treated $\times$ Swedish	0.001 (0.002)	-0.009*** (0.0003)	-0.0004 (0.0003)	0.0098*** (0.003)
Control mean	0.74	0.024	0.025	0.69
Observations	5,306,399	5,306,399	5,306,399	5,306,399
No of users	285,321	285,321	285,321	285,321

Employment results

	Log-earnings in recommended jobs		Prob to be hired (cond. on applying)			
	Migrants	Natives	Migrants		Natives	
	All hire	All hire	All hire	Lower Med	All hire	Lower Med
Treated	-0.005 (0.01)	-0.020* (0.012)	-0.002** (0.002)	-0.0029* (0.001)	-0.003*** (0.0012)	-0.002 (0.002)
High=1	-0.004 (0.012)	-0.0008 (0.012)	-0.001 (0.007)	-0.003 (0.002)	-0.001 (0.0012)	-0.002 (0.002)
Treated · High=1	0.0008 (0.017)	0.033* (0.016)	0.0018 (0.0016)	0.0048** (0.002)	0.0018 (0.002)	0.001 (0.002)
Control mean	9.92	9.97	0.015	0.018	0.018	0.021
Observations	1,093	1,599	78,740	47,545	95,066	44,904

Lower Med: occ. declared as searched has below median earnings

► Take away:

Fact 1: High increases the hiring quality of natives

Fact 2: High increases the hiring probability of migrants

Who are the newly hired?

- ▶ How can we rationalise the previous results?
 - ▶ Look at whether the composition of hired as changed

	Log-earnings, occ declared as searched			
	Migrants		Natives	
	<i>High</i> = 1	<i>High</i> = 0	<i>High</i> = 1	<i>High</i> = 0
Treated	-0.02** (0.008)	-0.009 (0.008)	-0.002 (0.008)	-0.014* (0.008)
Control mean	9.90	9.90	9.94	9.94
Observations	526	536	767	784

- ▶ Take away: Migrants from lower earnings are more often hired when pushed, therefore mitigating the average effect on earnings at hiring

Instrument - First Stage, Share of Migrants in the Firm

	Share of Migrants for Applications	
	Migrants	Natives
Treated	0.008*** (0.002)	0.011*** (0.002)
High=1	-0.0017 (0.002)	-0.001 (0.0015)
Treated · High=1	-0.013*** (0.003)	-0.009*** (0.002)
Control mean	0.31	0.22
Observations	77,694	94,346

$Z = 1$ if share of natives greater in treated vacancies than in control vacancies

- **Take away:** Job seekers comply, when $Z = 1$, they apply to firms with relatively more natives

Instrument - Second Stage, Share of Migrants in the Firm

	Share Migrants		P(h = 1 A)			
	Migrants	Natives	Migrants		Natives	
	All hire	All hire	All hire	Lower Med	All hire	Lower Med
Treated	0.002 (0.01)	-0.0007 (0.007)	-0.001 (0.001)	-0.001 (0.001)	-0.002 (0.001)	-0.002 (0.0002)
High=1	-0.006 (0.01)	0.003 (0.007)	-0.0001 (0.001)	-0.0019 (0.002)	-0.0006 (0.001)	-0.002 (0.002)
Treated · High=1	0.002 (0.015)	-0.01 (0.01)	0.002 (0.001)	0.0002 (0.002)	-0.0002 (0.001)	0.0002 (0.002)
Control mean	0.25	0.21	0.015	0.017	0.019	0.02
Observations	1,088	1,592	77,694	46,866	94,346	44,582