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Toy microsimulation of labour mismatch: a brief model description and demonstration

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March 29, 2024

General framework

Two-sided matching formulation by Zinn et al. (2012) adopted to static labour setting. Define

- a set of n **workers** i and a set of m **jobs** j (posted by the firms)
- s_i and r_j (respective elements of S and R) as **sets of attributes**
- a **compatibility measure** representing the quality of a match $c_{ij} = C(s_i, r_j)$, where $C : S \times R \to [0, 1]$; options:
  - a distance function *(selected)*
  - empirical likelihood of matching
- a **matching rule**; options:
  - Stable *(selected), e.g. Gale and Shapley's (1962) deferred acceptance procedure*
  - *Stochastic*, e.g. agents' c_{ij} has to be higher than randomly assigned "aspiration level" (i.e. expectations) for the match to occur

Preliminary demonstration (pre-alpha version) I

Monte Carlo simulation

- Data is generated using **simple DGPs**
- **Symmetric sets:** $n = m = 100$
- $1,000$ repetitions
- **Two attributes:**
  $s_i = \{education, skill\}$, $r_j = \{required\ education, required\ skill\}$
- **Same** $C(s_i, r_j)$ for both agent sets defined using a **distance function** that values the attributes equally
- **Decision rule:** an agent accepts the match if

$$U(c_{ij}, selectivity) \equiv c_{ij} - selectivity \geq 0 \tag{1}$$

where *selectivity* (aspiration in Zinn et al. (2012)) serves as a minimum compatibility threshold

Preliminary demonstration (pre-alpha version) II

Specifications:

- S_0 **Control:** DGPs specified below
- $S_{\dots}$ **Education policy (stylized):**
  - S_1 Workers have a 25% chance to increase their **skill** by $2\sigma_{skill}$
  - S_2 Workers have a 25% chance to increase their **education** by $2\sigma_{education}$
- $S_{\dots}$ **Change in labour demand (stylized):**
  - S_3 25% chance a firm increases its **skill requirement** by $2\sigma_{skill}$
  - S_2 25% chance a firm increases its **education requirement** by $2\sigma_{education}$

Workers I

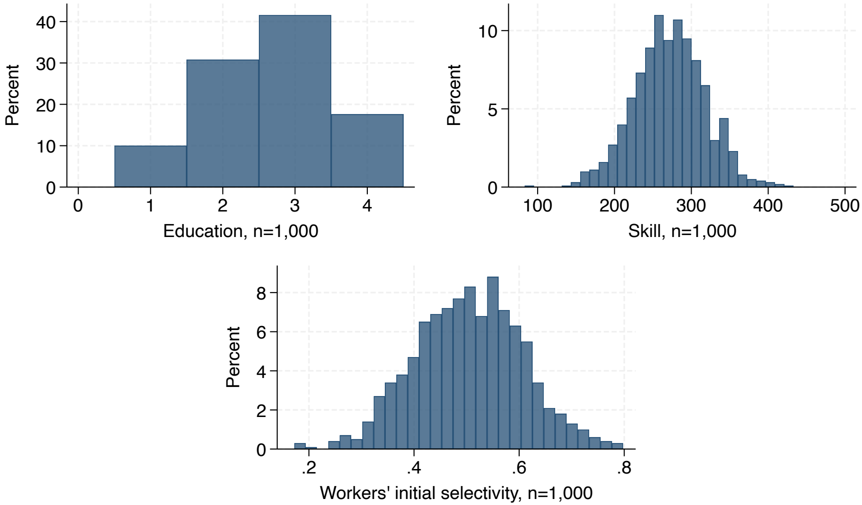
Attributes (inputs in compatibility measure)

- **Education:** mimics ISCO skill level, 4 categories, $\sim N(2.7, 0.9^2)$
- **Skill:** mimics PIAAC literacy scores, 500 points scale, $\sim N(272, 46^2)$

Other variables (used for matching procedure)

- **Selectivity:** $\in [0, 1]$, arbitrary, $\sim N(0.5, 0.1)$

Workers II


Percent
40
30
20
10
0
0 1 2 3 4
Education, n=1,000
Percent
10
5
0
100 200 300 400 500
Skill, n=1,000
Percent
8
6
4
2
0
.2 .4 .6 .8
Workers' initial selectivity, n=1,000

Jobs (Firms) I

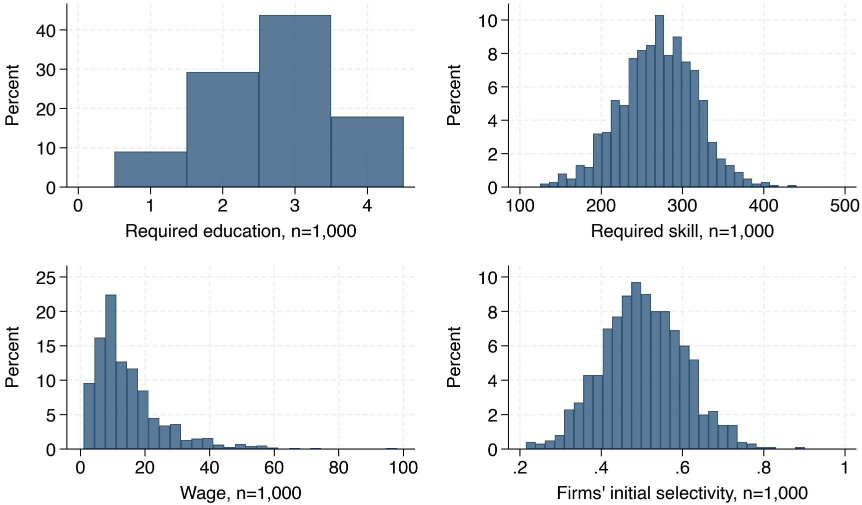
Attributes (inputs in compatibility measure)

- **Required education:** mimics ISCO skill level, 4 categories, $\sim N(2.7, 0.9^2)$
- **Required skill:** mimics PIAAC literacy scores, 500 points scale, $\sim N(272, 46^2)$

Other variables (used for matching procedure)

- **Selectivity:** $\in [0, 1]$, arbitrary, $\sim N(0.5, 0.1)$
- **Wage:** mimics hourly earnings including bonuses (USD PPP) $\sim LogNormal(2.45, 0.71^2)$

Jobs (Firms) II



Matching procedure I

In each iteration of the algorithm

1. Generate **network** – a subset of $k \sim N(n/2, (n/10)^2)$ jobs, of which the worker is aware
2. **Worker applies** for the highest-paying (if possible) unmatched job in their network
3. **Compatibility** of the potential match is calculated using a form of an exponential distance function (Perese, 2002)

$$C = \exp\left[-1.4 \times \sqrt{\left(\frac{edu - edu.req}{max_{edu}}\right)^2 + \left(\frac{skill - skill.req}{max_{skill}}\right)^2}\right] \quad (2)$$

Matching procedure II

4. Match occurs if $U(c_{ij}, selectivity_i) \geq 0$ and $U(c_{ij}, selectivity_j) \geq 0$, i.e. compatibility is **greater than both** worker's **and** firm's selectivity

5.1 If **match occurs**, then move on to the next worker

5.2 If **match fails** because
- **firm rejects** worker, then the worker's selectivity is reduced by 0.05
- **worker rejects** firm, then the firm's selectivity is reduced by 0.05
- **rejection is mutual**, then both worker's and firm's selectivity levels are reduced by 0.05

and the worker applies for the **next job** in the network

or the algorithm moves on to the **next worker** if there are no unapplied jobs left in the network

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The procedure terminates when all workers are matched

Matching procedure III

Special cases

- If either worker or job is **already matched**, then they use compatibility of the **current match** (instead of selectivity) to compare with the compatibility of the **potential match**
- If worker matches with a matched firm, the worker who is currently “employed” in that firm is “let go” and **no longer matched**
- When there are less than 10% of **unmatched jobs left**, they are guaranteed to be in a worker’s network and their selectivity is reduced by an additional 0.05

Labour mismatch measures

- **Realised Matches (RM):** worker is **well-educated** if their education is within $\pm$ one standard deviation from the mode of education for their occupation group

where **occupation:** 3 categories, function of skill, $\sim Beta(\alpha, \beta)$ with
  - $\alpha = 5 - (skill - \mu_{skill})/\sigma_{skill} \times 5$
  - $\beta = 5 + (skill - \mu_{skill})/\sigma_{skill} \times 5$

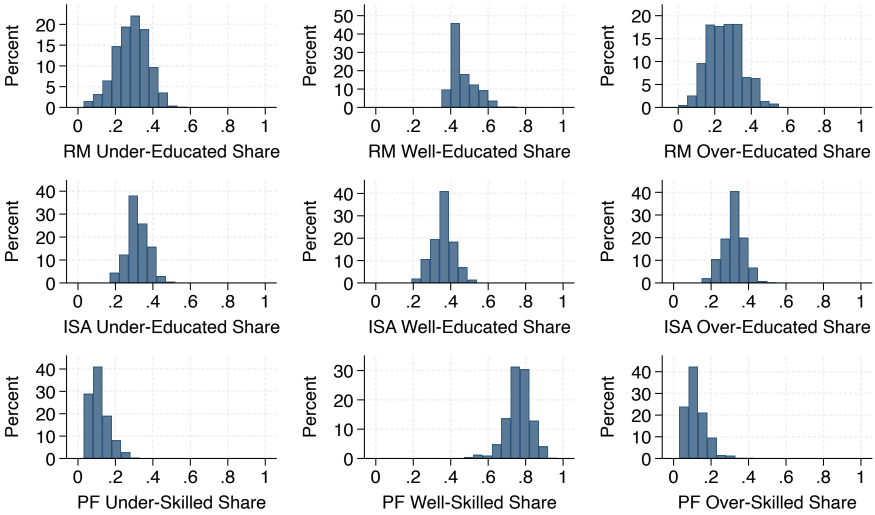
- **Indirect Self-Assessment (ISA):** worker is **well-educated** if their education matches firm's requirement
- **Pellizzari and Fichen (2017) (PF):** worker is **well-skilled** if their skill is within the 5th and 95th percentiles of the "well-matched" workers' skill distribution for their occupation group

where **"well-matched":** binary, $1(compatibility \geq \mu^{S_0}_{compatibility})$

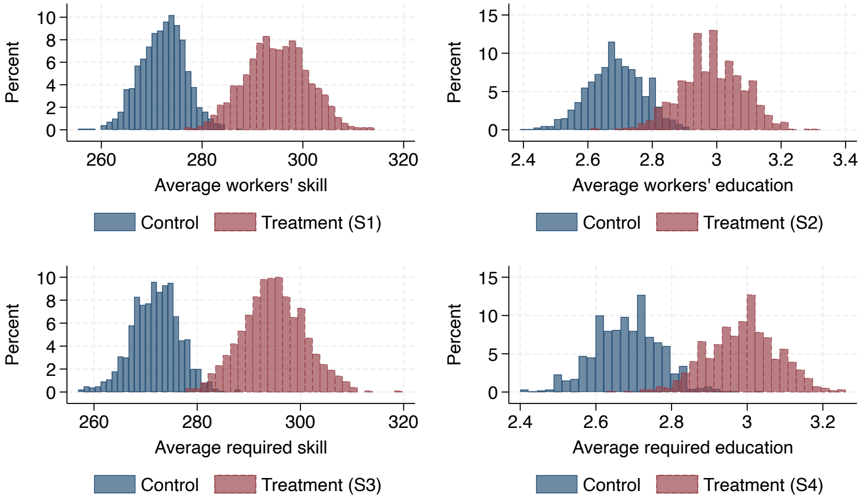
	μ_{skill}	percent
High-skill occupation	319	33.8
Mid-skill occupation	271	34
Low-skill occupation	224	32.2

	$\mu_{compat.}$	percent
Well-matched	0.89	34.4
Not well-matched	0.66	65.6

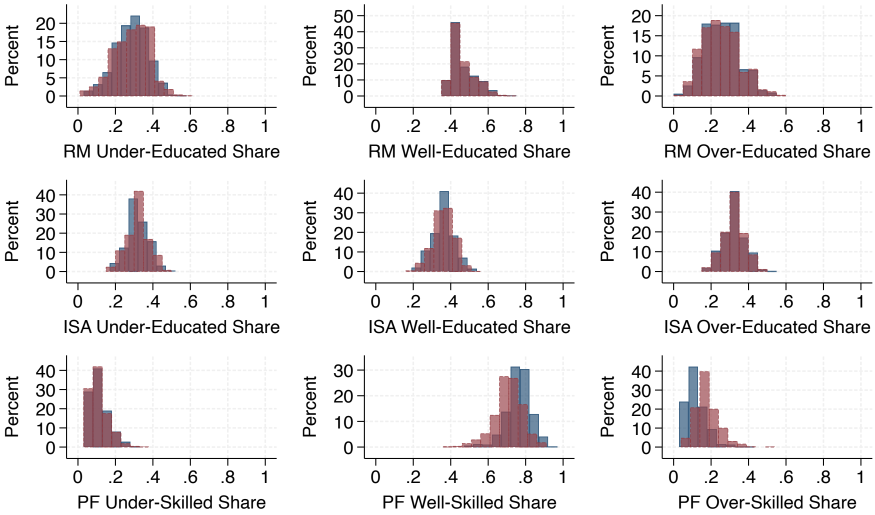
Mismatch measures output: Control (S_0)



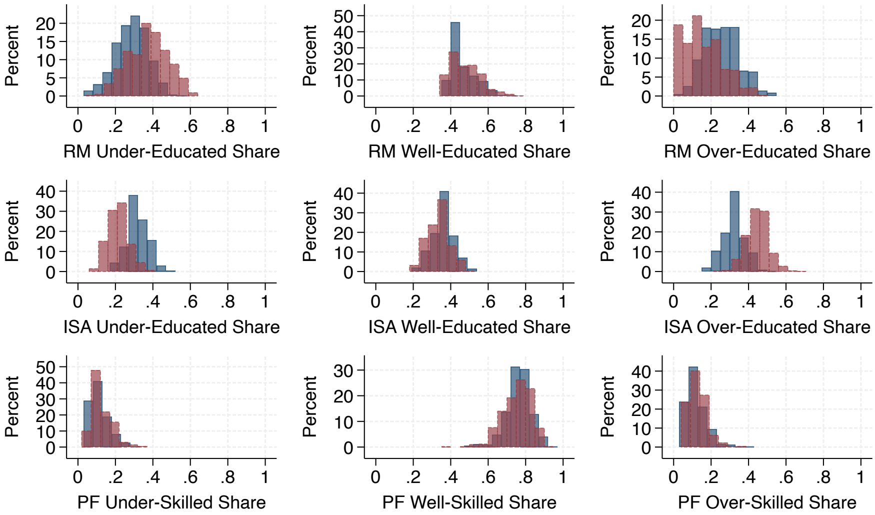
Treatments


Percent
10
8
6
4
2
0
260
280
300
320
Average workers' skill
Control
Treatment (S1)
Percent
15
10
5
0
2.4
2.6
2.8
3
3.2
3.4
Average workers' education
Control
Treatment (S2)
Percent
10
8
6
4
2
0
260
280
300
320
Average required skill
Control
Treatment (S3)
Percent
15
10
5
0
2.4
2.6
2.8
3
3.2
Average required education
Control
Treatment (S4)

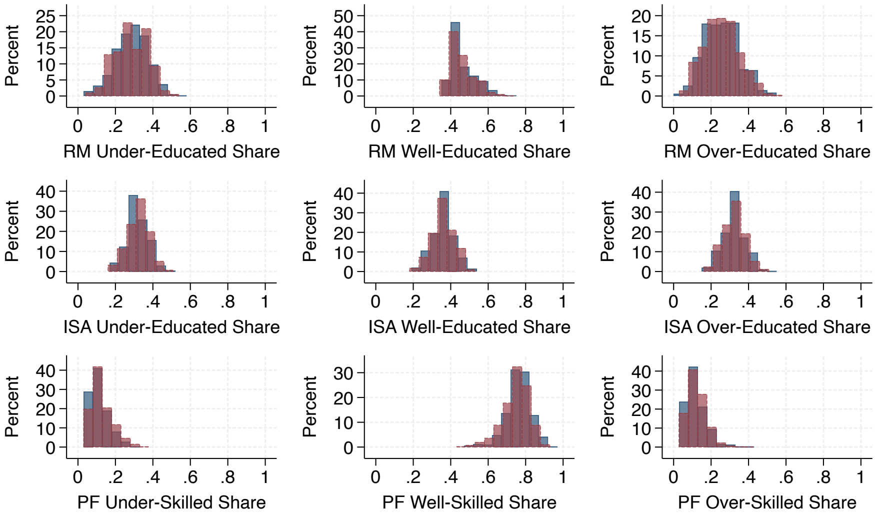
Education policy: skill $\uparrow$ (S_1)



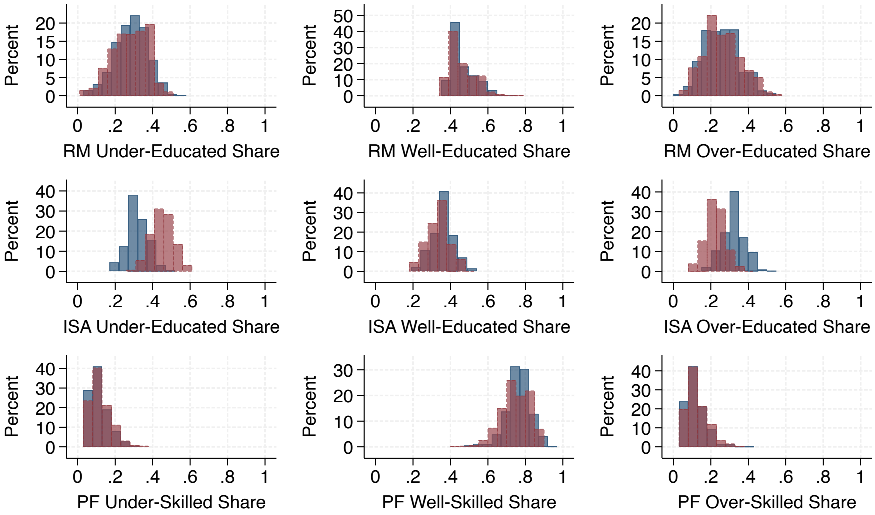
Education policy: education ↑ (S_2)



Change in labour demand: required skill ↑ (S_3)



Change in labour demand: required education ↑ (S_4)



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Pellizzari, M. and Fichen, A. (2017). A new measure of skill mismatch: theory and evidence from PIAAC. *IZA Journal of Labor Economics*, 6(1):1–30.

Perese, K. (2002). *Mate matching for microsimulation models*. Congressional Budget Office.

Zinn, S. et al. (2012). A mate-matching algorithm for continuous-time microsimulation models. *International journal of microsimulation*, 5(1):31–51.