General information for the conference

Welcome!

Wifi: you should have received an email

Lunch: 12:30pm everyday

Diner: 7:30pm

⇒ Special diner on Thursday: Bouillabaisse

Wed afternoon: free for all

⇒ Feel free to create a group for hiking

Hope you will have a nice and productive time!

PARIS ARTIFICIAL INTELLIGENCE FOR SOCIETY

Call for applications

Postdoctoral Fellowships 2024

Deadline for applications:
January 15, 2024 at noon

Hi! PARIS is pleased to announce and present our Call for Postdoctoral Fellowships.

Hi! PARIS is the new interdisciplinary Center on Data Analytics and Artificial Intelligence for Science, Business and Society created by Institut Polytechnique de Paris (IP Paris) and HEC Paris and recently joined by Inria (Centre Inria de Saclay). One of the central aims of Hi! PARIS is to **conduct breakthrough and multidisciplinary research on AI and Data Science**.

Market Design for Distributional Objectives in (Re)assignment: An Application to Improve the Distribution of Teachers in Schools

Julien Combe
CREST & École Polytechnique

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NC State U

Olivier Tercieux
CNRS & PSE

Camille Terrier
QMUL

Utku Ünver
Boston College

under revision

From matching to markets
CIRM - Marseille

Dec 11-15, 2023

Centralized (Re)assignment

Centralized (re)assignment involves

first time assignment of new workers to jobs together with reassignment of senior workers who would like to move to a different job.

Examples:

Government Sector: Police officers (e.g. Chicago), doctors (many countries), administrators (e.g. India), teachers (many countries)
Private Sector: Job rotations (many large corporations)

Common features:

1. One or few large employers are in charge of jobs.
2. Workers have preferences over jobs.
3. Employers have distributional objectives
4. Senior workers can stay at their job or move to a better one; new workers need a first-time job.

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Distributional Goals and Centralized (Re)assignment

Distributional objectives exist, yet can sometimes be in conflict with agents preferences.

Examples:

- Senior police officers shy away from urban areas, CPD needs more officers in urban areas due to disproportionate crime rates (Sidibe et al., 2021).
- Indian civil servants often get assigned close to their home states, while the government needs them to be distributed around for national integration (Thakur, 2020).
- Main application in this paper:
- Disadvantaged regions have relatively more inexperienced teachers; to decrease the education achievement gap in the country, more experienced teachers are needed in these regions.
  - Empirical evidence points that experience level of teachers positively affect education outcomes.
    (Chetty, Friedman, Rockoff, 2014 – in the U.S.)
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Example: Teacher Distribution in France

Figure: Share of students in a disadvantaged school

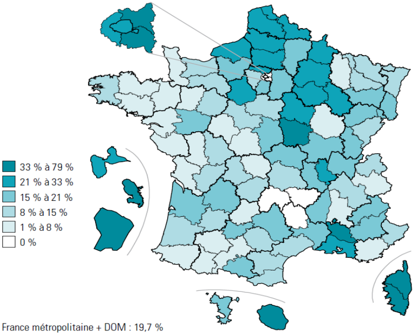
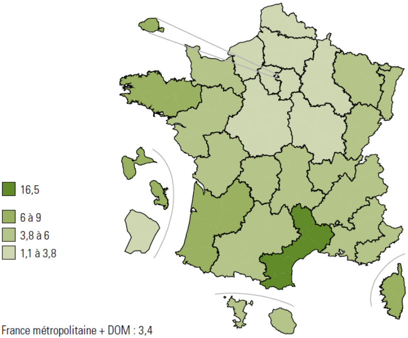


Figure: Ratio of teachers age 50+ to age 30–



Contribution

Contribution 1: We propose a new mechanism which incentivizes truthful reports from teachers and improves both schools and teachers with respect to a status-quo matching. A school improvement is measured by a (Lorenz) shift of the types' distribution of its assigned teachers following a priority ordering over types (e.g. ranking over exp. levels)

Contribution 2: In a large market setting, we show how a global objective of decreasing inequalities across schools can be achieved by designing priorities for schools and using our proposed mechanism to shift their types' distribution

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2 Model

3 School priorities and Lorenz Dominance

4 SI-CC mechanism and its properties

5 Priority design for inequality reduction

6 Empirical analysis (short version)

7 Conclusion

The Model

T: set of n teachers

N: set of new teachers

$T \setminus N$: set of tenured teachers

Types: t has an experience level $\theta(t) \in \Omega \subset \mathbb{R}$ where Ω is finite

S: set of m schools, each school s with quota q_s.

ω: status-quo matching is the initial allocation

- $\omega_t \in S \cup \{\emptyset\}$: the initial school of teacher t
- $\omega_t = \emptyset \iff t$ is a new teacher
- $\omega_s \subseteq T$: the initial employees of school s

P_t: strict preference relation of teacher t over $S \cup \{\emptyset\}$

Inequality reduction: priorities v.s. global objective

Main objective: reduce inequalities across schools

⇒ Global objective that is complex

Priority design: how to achieve the global objective of inequality reduction using priorities for each school?

⇒ Intuition: "shift up" the distrib. of schools with low exp. and "shift down" the one of schools with high exp.

Simpler: improve each school's distribution of experience according to some fixed priority ordering over experience levels

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School Priorities and Lorenz Dominance

$\triangleright_s$: priority over teacher types for school s (a linear order)

Comparisons over sets of teachers are based on Lorenz comparison, i.e., using first-order stochastic dominance of type distributions assigned:

For any two sets of teachers $\bar{T}, \hat{T}$

$$\forall \theta \quad \sum_{\theta' \trianglerighteq_s \theta} \#\ \text{type-}\theta'\text{teachers in } \bar{T} \geq \sum_{\theta' \trianglerighteq_s \theta} \#\ \text{type-}\theta'\text{teachers in } \hat{T}$$

$$\iff \qquad \bar{T} \succsim_s \hat{T}$$

$\Longrightarrow$ Will be justified by priority design for inequality reduction (next section).

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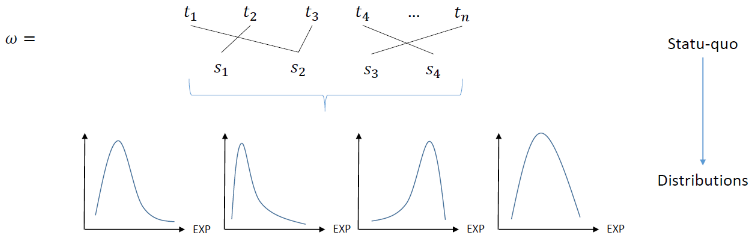

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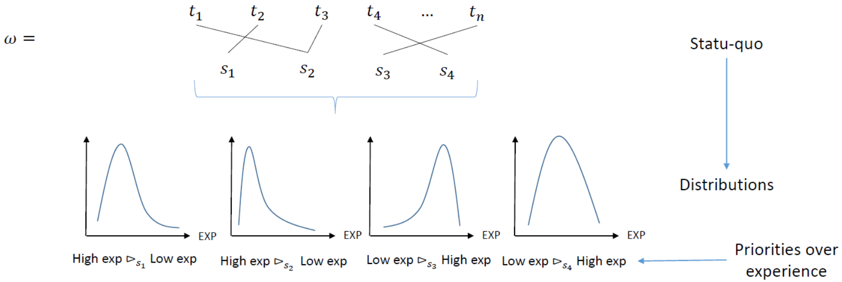

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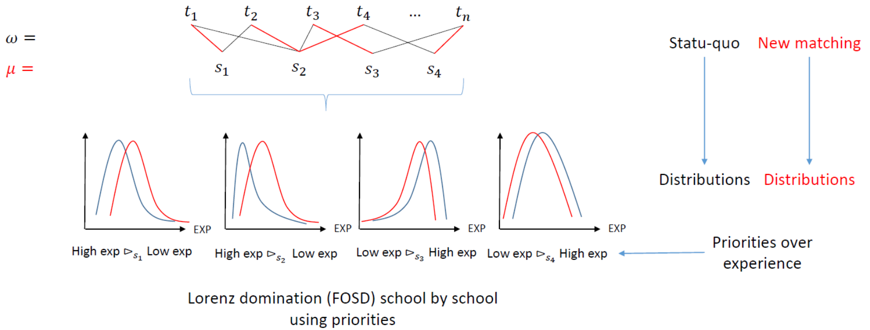

Mechanisms and Key Properties

A mechanism φ maps teacher preferences to matchings

φ is individually rational (IR) if for every profile P,

$$\text{for every teacher } t \quad \varphi_t(P)\ R_t\ \omega_t.$$

φ is school improving (SI) if for every profile P and school s: $\varphi_s(P) \succsim_s \omega_s$ (Lorenz domination)

$\Rightarrow$ With the right priority $\rhd$: decreases ineq. accross schools

φ is strategy-proof (SP) if for every profile P, teacher t, and manipulation $\hat{P}_t$: $\varphi_t(P_t, P_{-t})\ R_t\ \varphi_t(\hat{P}_t, P_{-t})$.

φ is constrained efficient if

- it improves both teachers and schools (IR+SI)
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SI Cycles and Chains (SI-CC) Mechanism

School pointing rule: Each school points to its employees in reverse order of its priority ranking (using a fixed tie breaker).

Teacher pointing rule: Each teacher t points to her top-choice school s such that

either

Replacing the teacher that school s is pointing with teacher t weakly improves school s w.r.t. the status quo

or

school s has a vacant seat.

Chain construction & selection rule: Only chains

beginning with a new teacher and

ending at a school with a vacant position

are selected (when no SI cycle exists), so that schools do not lose employees without replacing them.

Formal Definition Skip the SI-CC Example

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SI-CC Example

4 schools: s_1, s_2, s_3, s_4

$q_{s_1} = q_{s_3} = 2$ and $q_{s_2} = q_{s_4} = 1$

3 teacher types: high (h), medium (m), low (ℓ) experiences

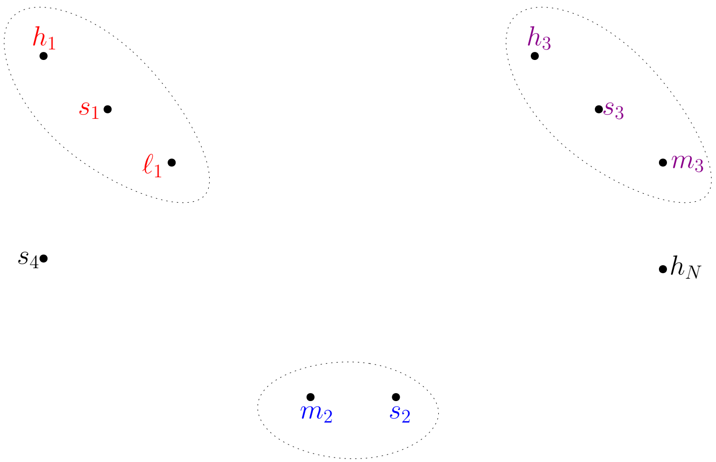
6 teachers: 3 high , 2 medium , 1 low type

status-quo matching:

- h_1 and ℓ_1 at s_1
- m_2 at s_2
- h_3 and m_3 at s_3
- h_N new teacher
- no teacher at s_4

h_1	ℓ_1	m_2	h_3	m_3	h_N
s_4	s_2	s_4	s_1	s_2	s_2
s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
	m	m	m	m
	ℓ	ℓ	h	h
status quo:	h_1, ℓ_1	m_2	m_3, h_3	$\emptyset$
current:	h_1, ℓ_1	m_2	m_3, h_3	$\emptyset$



h_1	ℓ_1	m_2	h_3	m_3	h_N
s_4	s_2	s_4	s_1	s_2	s_2
s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
	m	m	m	m
	ℓ	ℓ	h	h
status quo:	$h_1, \underline{\ell_1}$	$\underline{m_2}$	$m_3, \underline{h_3}$	$\emptyset$
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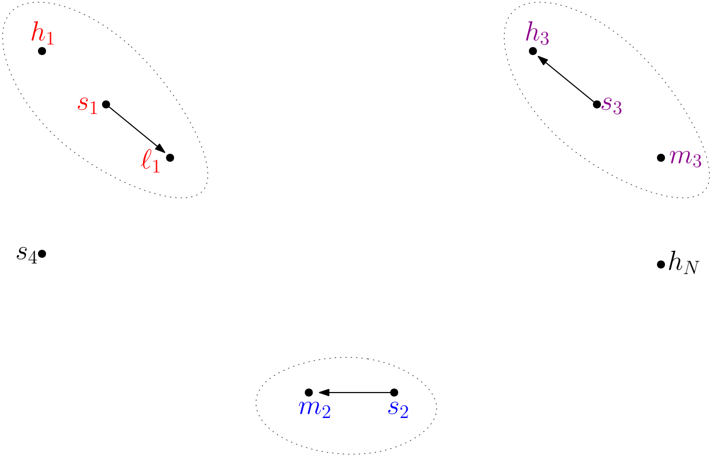

h_1	ℓ_1	m_2	h_3	m_3	h_N
s_4	$\cancel{s_2}$	s_4	s_1	s_2	s_2
s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
	m	$\boxed{m}$	m	m
	ℓ	$\boxed{\ell}$	h	h
status quo:	$h_1, \underline{\ell_1}$	$\underline{m_2}$	$m_3, \underline{h_3}$	$\emptyset$
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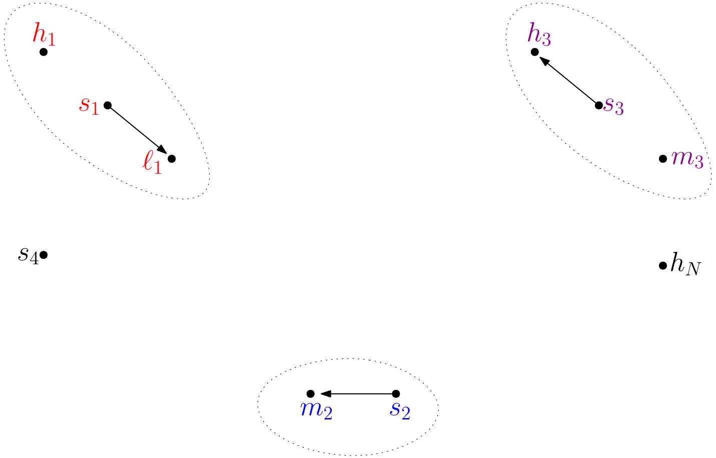

h_1	ℓ_1	m_2	h_3	m_3	h_N
$\underline{s_4}$	$\cancel{s_2}$	$\underline{s_4}$	$\underline{s_1}$	$\underline{s_2}$	$\underline{s_2}$
s_2	$\underline{s_3}$	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
	m	m	m	m
	ℓ	ℓ	h	h
status quo:	$h_1, \underline{\ell_1}$	$\underline{m_2}$	$m_3, \underline{h_3}$	$\emptyset$
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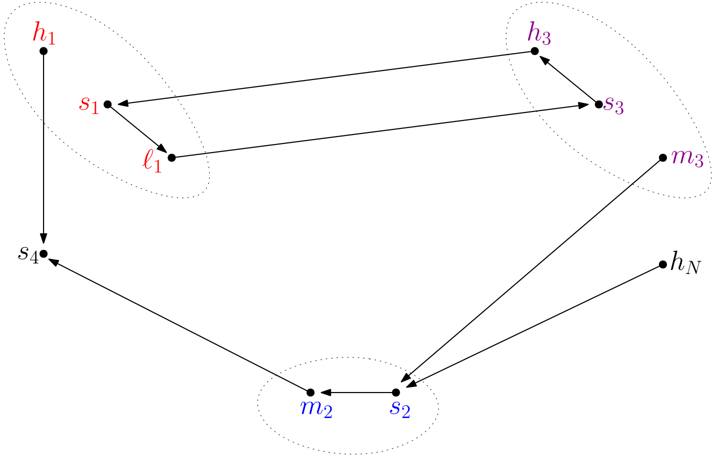

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$\underline{s_4}$	$\cancel{s_2}$	$\underline{s_4}$	$\underline{s_1}$	$\underline{s_2}$	$\underline{s_2}$
s_2	$\underline{s_3}$	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
	m	m	m	m
	ℓ	ℓ	h	h
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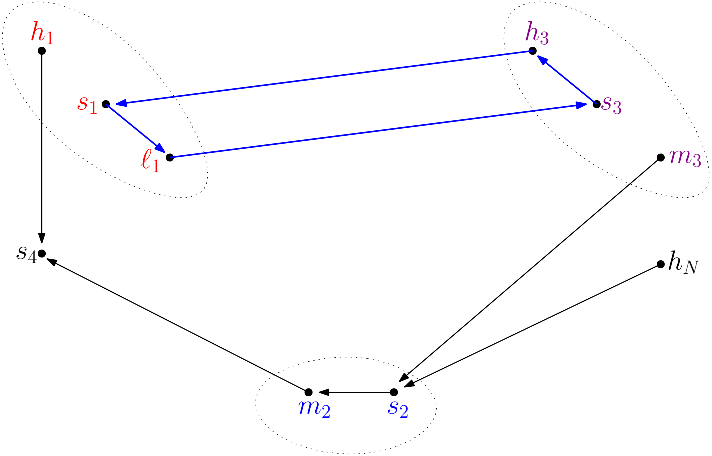

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s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
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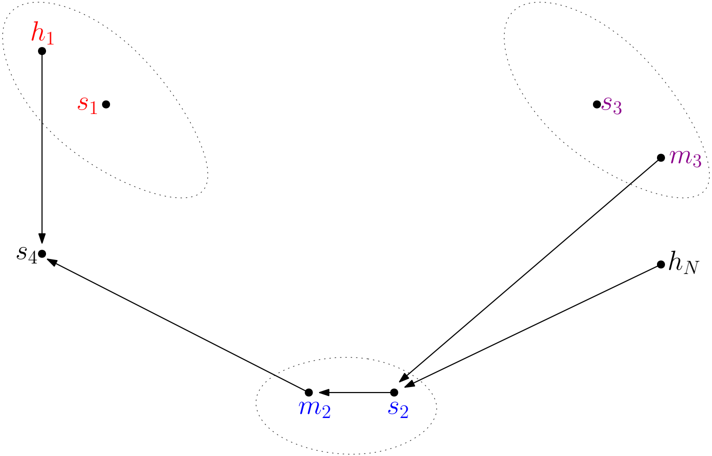

h_1	ℓ_1	m_2	h_3	m_3	h_N
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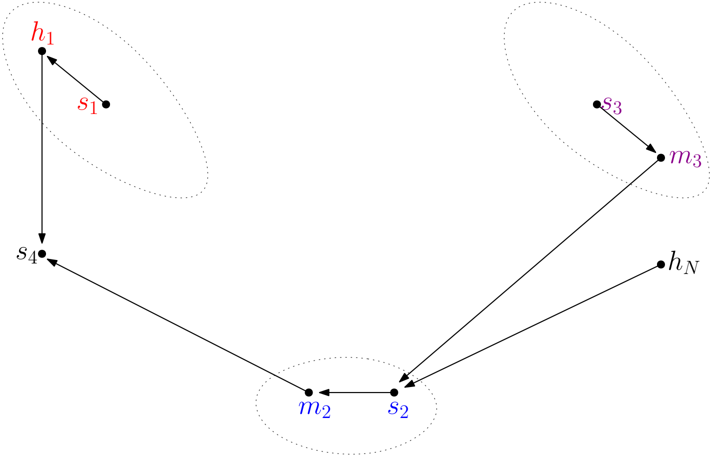
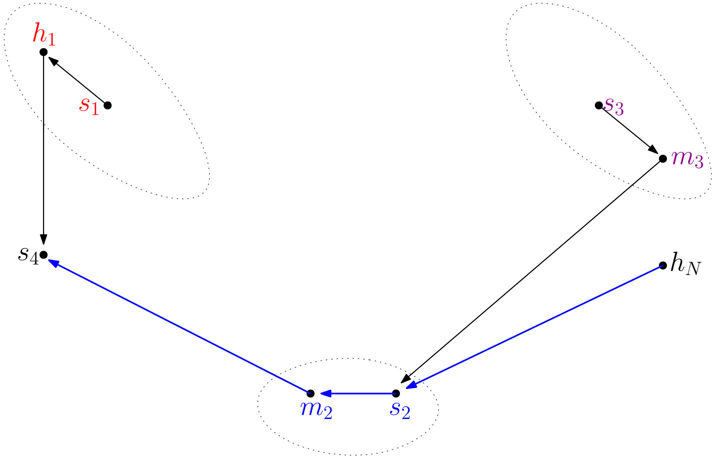
s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
	m	m	m	m
	ℓ	ℓ	h	h
status quo:	$\underline{h_1}, \ell_1$	$\underline{m_2}$	$\underline{m_3}, h_3$	$\emptyset$
current:	h_1, h_3	m_2	ℓ_1, m_3	$\emptyset$



h_1	ℓ_1	m_2	h_3	m_3	h_N
$\underline{s_4}$	$\cancel{s_2}$	$\underline{s_4}$	s_1	$\underline{s_2}$	$\underline{s_2}$
s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
	m	m	m	m
	ℓ	ℓ	h	h
status quo:	$\underline{h_1}, \underline{\ell_1}$	$\underline{m_2}$	$\underline{m_3}, h_3$	$\emptyset$
current:	h_1, h_3	m_2	ℓ_1, m_3	$\emptyset$



h_1	ℓ_1	m_2	h_3	m_3	h_N
s_4	$\cancel{s_2}$	s_4	s_1	s_2	s_2
s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
	m	m	m	m
	ℓ	ℓ	h	h
status quo:	$\underline{h_1}, \ell_1$	m_2	$\underline{m_3}, h_3$	$\emptyset$
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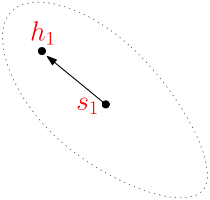

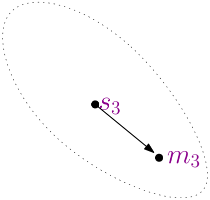

h_1	ℓ_1	m_2	h_3	m_3	h_N
s_4	$\cancel{s_2}$	s_4	s_1	s_2	s_2
s_2	s_3	s_3	s_3	$\underline{s_1}$	s_1
$\underline{s_3}$	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
	m	m	m	m
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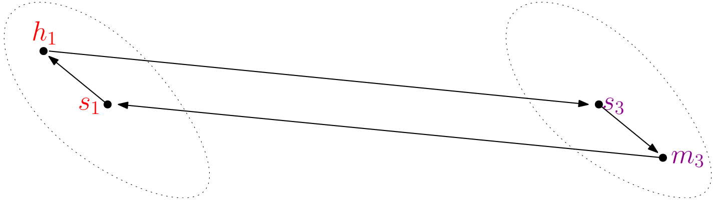

h_1	ℓ_1	m_2	h_3	m_3	h_N
s_4	$\cancel{s_2}$	s_4	s_1	s_2	s_2
s_2	s_3	s_3	s_3	$\underline{s_1}$	s_1
$\underline{s_3}$	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
	m	m	m	m
	ℓ	ℓ	h	h
status quo:	$\underline{h_1}, \ell_1$	m_2	$\underline{m_3}, h_3$	$\emptyset$
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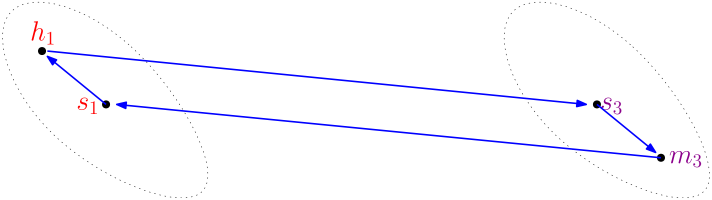

h_1	ℓ_1	m_2	h_3	m_3	h_N
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s_2	s_3	s_3	s_3	s_1	s_1
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s_1	s_4	s_1	s_4	s_4	s_4

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SI Cycles and Chains (SI-CC) Mechanism

School pointing rule: Pointing to lower ranked teachers first: important for strategy-proofness

Teacher pointing rule: Need a counter at each school to keep track of improvements to determine whether a teacher can point

Chain construction & selection rule: Ensure SI by not leaving occupied seats empty

Main Result

Theorem

The SI-CC mechanism is strategy-proof and constrained-efficient (IR & SI)

Remark

Any change in pointing rules in SI-CC (except tie-breaking) may lead to a violation in either SI, constrained efficiency, or strategy-proofness.

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Priority Design for Inequality Reduction

A matching $\mu \Rightarrow$ total distrib. of experience $d^\mu = (d_s^\mu)_s$

Distrib. of exp. $d^\mu \Rightarrow$ statistics for schools $f(d^\mu) \in \mathbb{R}^m$

Example: average experience in each school

Property: must be increasing with Lorenz domination (FOSD)

Stats for schools $f(d^\mu) \Rightarrow$ inequality index $I(f(d^\mu)) \in \mathbb{R}$

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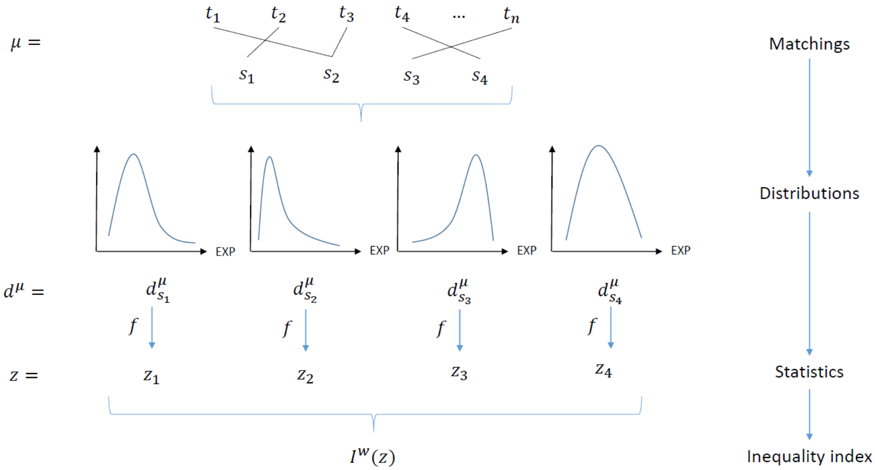

Priority Design for Inequality Reduction

Inequality index $I(f(d^{\mu}))$: Schur-convex and cont. differentiable a.e.

Example: Gini Index

$$I(z) = \frac{1}{2\sum_s w_s z_s} \sum_s \sum_{s'} w_s w_{s'} |z_s - z_{s'}| \text{ at } z = f(d^{\mu})$$

Reducing inequalities:

$$I\big(f(d^{\mu})\big) \leq I\big(f(d^{\omega})\big)$$

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Large Market and Inequality Reduction

ν^j the matching of j teachers outside of the reassignment market

$\Rightarrow$ Stat. are computed using all teachers

Assumption (f-convergence)

For any matching μ and school s, $f(d^{\mu,j}) \xrightarrow{j\to\infty} z^*$

$\Rightarrow$ The impact of the matching μ on the stat. is small
when the number of outside teachers is large

E.g. in France $\approx 2\%$ ask for a reassignment

School improvement for $\rhd^*$ $\Rightarrow$ Inequality reduction

Proposition

Under f-convergence, for a large enough market size j, there exists priorities for schools $\rhd^*$ such that if μ is school improving, then μ reduces inequalities

Sketch: "increase bad schools and decrease good schools"

Partition the set of schools in two groups L and H:

$s \in L$ if $\frac{\partial I}{\partial z_s}(d_s^\omega) < 0$

$\Rightarrow$ Increasing the stat. for s **decreases** inequalities

$s \in L$ if $\frac{\partial I}{\partial z_s}(d_s^\omega) > 0$

$\Rightarrow$ Increasing the stat. for s **increases** inequalities

Priority design. define priorities $\rhd^*$ over types:

For each school $s \in L$, $\theta_{|\Theta|-1} \rhd_s^* \theta_{|\Theta|-2} \rhd_s^* \ldots \rhd_s^* \theta_1 \rhd_s^* \theta_0$

$\Rightarrow$ L schools prefer high to low exp.

For each school $s \in H$, $\theta_0 \rhd_s^* \theta_1 \rhd_s^* \theta_2 \rhd_s^* \ldots \rhd_s^* \theta_{|\Theta|-1} \rhd_s^*$

$\Rightarrow$ H schools prefer low to high exp.

Sketch: "increase bad schools and decrease good schools"

Partition the set of schools in two groups L and H:

$s \in L$ if $\frac{\partial I}{\partial z_s}(d^\omega) < 0$ but $\exists \mu : \frac{\partial I}{\partial z_s}(d^\mu) > 0$?

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Inequality reductions $\Rightarrow$ school improvement w.r.t. $\triangleright^*$

Consider a class of statistics $\mathcal{E}$

$\Rightarrow$ We want to reduce inequalities for all of them: "robustness"

Proposition (informal)

If the class $\mathcal{E}$ is rich then for a large enough market size j, μ reduces inequalities for all $f \in \mathcal{E} \Rightarrow \mu$ statu-quo improves ω w.r.t. to $\triangleright^*$

Corollary (informal)

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Finite markets and SI-CC

Proposition

There is no mechanism that is strategy-proof and generates lower inequalities than SI-CC whenever possible

Related Literature

Centralized teacher (re)assignment, and other jobs:

Pereyra (2013); Combe, Tercieux, Terrier (2021); Dur & Kesten (2019); Agarwal (2015); Thakur (2020); Sidibe et al., (2021) ...

Efficient matching and constraints:

Shapley & Scarf (1974); Abdulkadiroğlu & Sönmez (1999); Papai (2000); Roth, Sönmez, Ünver (2004); Dur, Kesten, Ünver (2015); Pycia & Ünver (2017); Takamasa, Tamura, Yokoo (2018); Dur & Ünver (2019); Hafalır, Kojima, Yenmez (2022) ...

Stable/fair matching and constraints:

Gale & Shapley (1962); Kelso & Crawford (1982); Roth & Sotomayor (1990); Balinski & Sönmez (1999); Abdulkadiroğlu & Sönmez (2003); Hatfield & Milgrom (2005); Kominers & Sönmez (2016); Hafalır, Yenmez, Yıldırım (2013); Ehlers et al. (2014); Kojima & Kamada (2015, 2016); Dur et al. (2018, 2020); Sönmez & Yenmez (2022) ...

Unequal distribution of teachers across schools:

Bobba et al. (2021); Bates et al. (2021); Biasi et al. (2021); Tincani (2021) ...

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French teacher assignment

Data on French centralized assignment of teachers to regions in 2013

Estimation of teachers' pref over regions: $u_{t,R}$ Details

Separate estimation for tenured teachers and newcomers

Estimation on each of 8 fields (Maths, History, Sport...)

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Aims to quantify the algorithms performance in a real-life setting:

- SI-CC (our SI constrained efficient mechanism)
- Benchmark for SI-CC: TTC*
  - As SI-CC but does not impose status-quo improvement for schools ($\sim$ school choice TTC with IR).
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Teacher Types and Regions' Preferences

Teacher type:

- Corresponds to her experience
- We classify teachers into 13 experience bins

Inequality index and schools' priorities

- We use the Gini index together with the mean experience statistic in each region
- We follow the priority design construction from the theory

		Regions	Teacher-Type Ranking $\rhd$
1	L = Gini derivative < 0	Créteil Versailles Amiens...	High exp $\rhd \ldots \rhd$ Low exp $\rhd\ \emptyset$
2	H = Gini derivative > 0	Bordeaux Rennes Lyon...	$\emptyset \rhd$ Low exp $\rhd \ldots \rhd$ High exp

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Empirical results: SICC decreases inequalities

	Statu-quo (1)	SI-CC (2)	TTC* (3)	Current French (4)
		Panel A. Teacher mobility		
Mobility	-	5,221	6,393	5,866
... From L regions	-	798	1,843	1,547
... From H regions	-	512	639	407
... Tenured	-	1,310	2,481	1,954
... Newcomers	-	3,912	3,912	3,912
Number of unassigned teachers	-	715	715	715
		Panel B. Average rank of region obtained		
Average rank of assigned region	16,28	7.58	7.31	8.27
... Teachers from the L regions	8.3	7.28	5.67	6.15
... Teachers from the H regions	9.4	4.71	3	5.39
... Tenured	8.47	6.91	5.29	6.04
... Newcomers	26	8.42	9.85	11.08
		Panel C. Inequalities		
Gini index	0.048	0.047	0.051	0.051
Average exp. in L regions	11.98	12.05	11.94	11.96
Average exp. in H regions	14.01	13.99	14.11	14.10

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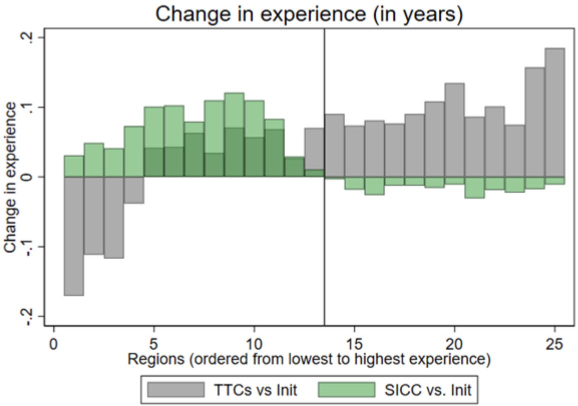

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We design schools' priorities that reflect a central authority's welfare objective, here: reduce inequalities

We design a mechanism SI-CC that improve both teachers welfare and schools' welfare (proxy to reduce ineq.) compared to an initial allocation.

Our counterfactual analysis using French data shows that

- SI-CC reduces inequalities across regions
- While ensuring a high teacher mobility Other benchmarks
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$\Rightarrow$ Interesting for future research

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Appendix

SI Cycles and Chains Mechanism

Step k:

Each remaining school s points to its remaining least preferred statsus-quo employee (if there are many, it uses a fixed tie-breaker). Each remaining teacher t points to her top choice among $\emptyset$ and all remaining schools s that satisfy:

Type (1) School improvement by replacement: if s points to a teacher t' and replacing her with t will make s weakly better off than its status quo assignment,

or

Type (2) School improvement by addition: if t is acceptable for s and s has a vacant seat.

$\emptyset$ points to all teachers pointing to it.

SI Cycles and Chains Mechanism

Step k continued:

Two cases:

(i) There exists a cycle in which
either all teachers' pointing satisfies (1)
or there are only one teacher and option $\emptyset$

Each teacher is assigned to the school/option she is pointing to, go to Step k+1.

(ii) There exists a chain and (i) does not hold.

- If there is a remaining new teacher: we select a starting with the new teacher and ending with a school with a vacant position
- Otherwise: we remove each school s whose all status-quo employees are assigned, go to Step k+1.

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Demand estimation

Random utility model estimated as a function of teachers' and regions' characteristics

$$u_{t,R} = \delta_R + Z'_{t,R}\beta + \varepsilon_{t,R} \quad (1)$$

δ_R	region fixed effect
$Z_{t,R}$	teacher-region-specific observables
$\varepsilon_{t,R}$	random shock i.i.d. over t and R
	type-I extreme value distribution, Gumbel(0,1)

Goal: Estimate the model and run counter-factuals

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Demand estimation

Teacher characteristics:

- Qualification
- Experience
- Family status

Teacher-region specific characteristics:

- Birth region
- Current region

(Interacted) Region characteristics:

- Socio-economic measure
- Academic performance measure
- ...

Preference estimation

Identifying assumption based on stability
(Chiappori-Salanié (16), Akyol-Krishna (17), Artemov-Che-He (19), Fack-Grenet-He (19))

> Teachers might skip unreachable regions from their ranking
> **but**
> Assignment = most preferred region within feasible regions

Logit choice probabilities. Estimate β via ML.

Fit is a lot better than assuming truthtelling Back.

Eight markets

	All teachers	Newcomers	Initially assigned	Vacant positions
	(1)	(2)	(3)	(4)
All subjects	10460	4627	5833	3912
Sport	2066	568	1498	475
French	1645	786	859	663
English	1374	746	628	640
Mathematics	1563	958	605	824
Spanish	999	316	683	248
History-Geography	1230	657	573	562
Biology	746	286	460	246
Physics-Chemistry	837	310	527	254

Teachers' characteristics

	Tenured			Newcomers		
	French (1)	Math (2)	English (3)	French (4)	Math (5)	English (6)
% Female	76.1	47.0	85.4	80.3	41.7	80.4
% Maried	48.5	45.0	46.8	41.1	39.4	40.9
% In disadvantaged school	10.4	13.2	4.4	0.0	0.0	0.0
Experience (in years)	7.48	7.23	7.18	2.76	2.24	2.30
% Advanced teaching qualif	7.9	29.1	8.8	16.8	31.7	15.2
Observations	859	605	628	786	958	746

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