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

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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.

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:

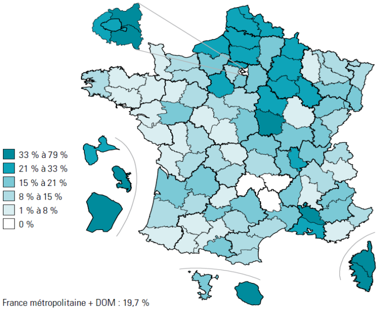
    Disadvantaged regions have relatively more inexperienced teachers; to decrease the education achievement gap in the country, more experienced teachers are needed in these regions.
    - Empirical evidence shows that teacher experience positively affects education outcomes.

      (Chetty, Friedman, Rockoff, 2014 – in the U.S.)

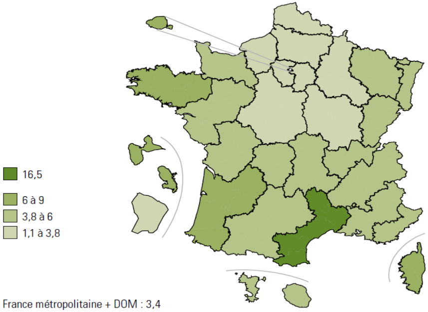
      (Allen, Mian, Sims, 2016 – in the U.K.)

Example: Teacher Distribution in France

Share of students in
a disadvantaged school



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 type distribution of its assigned teachers following a priority ordering over types (e.g., a ranking over experience levels).
- **Contribution 2**: In a large market setting, we show how a global objective of decreasing inequality across schools can be achieved by designing priorities for schools and using our proposed mechanism to shift their teacher type distribution.
- **Contribution 3**: Using French data, we conduct empirical simulations:
  - Our mechanism achieves a decrease in inequality while other benchmarks do not, notably those without distributional objectives.

The Model

- T: set of teachers
  N: set of new teachers
  $T \setminus N$: set of tenured teachers
  Types: t has a teacher type $\theta(t) \in \Theta$ finite
  - Example: $\theta(t) =$ experience in years
- S: set of schools, each school s with a 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 $S \cup \{\emptyset\}$
- Allocation: A matching is an assignment of teachers to schools so that
  - each teacher is matched with at most one school, and
  - each school does not exceed its quota.

Mechanisms

- A mechanism φ maps teacher preferences to matchings.
- φ is individually rational (IR) if for every profile P and teacher t,

$$\varphi_t(P)\ R_t\ \omega_t.$$

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

$$\varphi_t(P_t, P_{-t})\ R_t\ \varphi_t(\hat{P}_t, P_{-t}).$$

Inequality Reduction: Priorities vs. Global Objective

- Main objective: reduction of inequality across schools
  $\Rightarrow$ 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 distributions of schools with low experience
    and
    "shift down" the distributions of schools with high experience

  - Simpler:
    Improve each school's distribution of experience according to some fixed priority order over experience levels

Type Rankings and Status-quo Improvement

- $\triangleright_s$: A type ranking for school s is a linear order over teacher types.

- 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 $\bar{T}, \hat{T}$ if

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

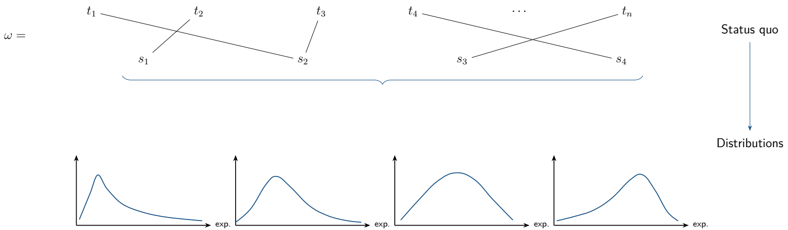
  then $\bar{T}$ $\triangleright_s$-Lorenz dominates $\hat{T}$.

- A mechanism φ is $\triangleright$-status-quo improving ($\triangleright$-SI) if for every profile P and school s,

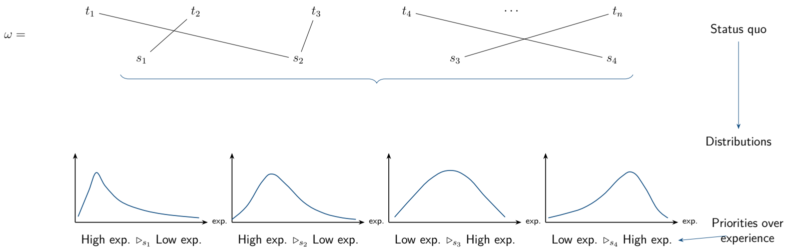
  $$\varphi_s(P) \ \triangleright_s\text{-Lorenz dominates } \ \omega_s.$$

- Where do we use it?
  - This approach will be justified by type ranking design for inequality reduction.

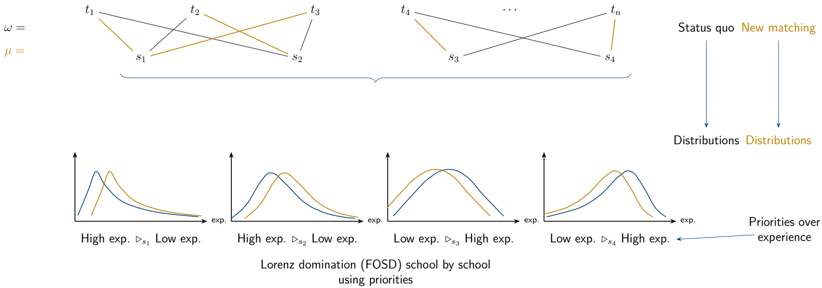
Type Rankings and Status-quo Improvement



Type Rankings and Status-quo Improvement



Type Rankings and Status-quo Improvement



Constrained Efficient Mechanisms

- A mechanism φ is $\triangleright$-constrained efficient if
  - it is IR and $\triangleright$-SI, and
  - for every profile P, $\varphi(P)$ is not Pareto dominated (for teachers) by another IR and $\triangleright$-SI matching.

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.

SI-CC Mechanism

Given type ranking profile $\triangleright$:

- Step k:
  - Each remaining school s points to its remaining lowest type status-quo employee under $\triangleright_s$ (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 the current match of s to $\triangleright_s$-Lorenz dominate ω_s,

or

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

  - $\emptyset$ points to every teacher pointing to it.

SI-CC Mechanism

- Step k continued:

  Two cases:

  (i) There exists a cycle in which
  either every teacher's 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 chain starting with a new teacher (using a fixed tiebreaker) 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.

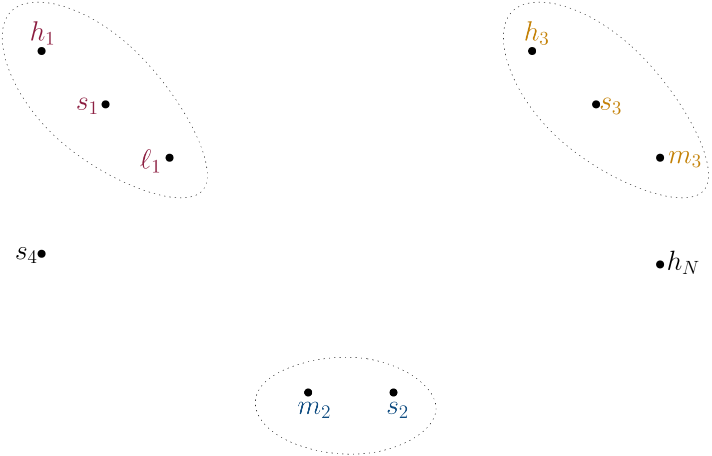
Skip the SI-CC Example

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

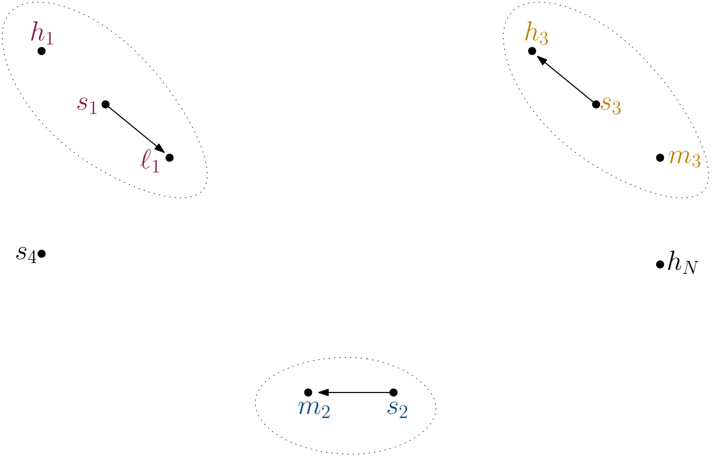
h_1	ℓ_1	m_2	h_3	m_3	h_N
s_4	s_2	s_4	s_1	s_2	s_2
s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	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	$\emptyset$



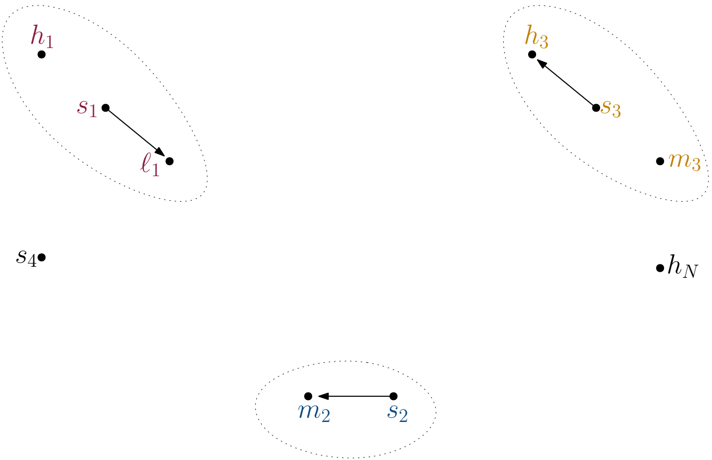
h_1	ℓ_1	m_2	h_3	m_3	h_N
s_4	s_2	s_4	s_1	s_2	s_2
s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

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



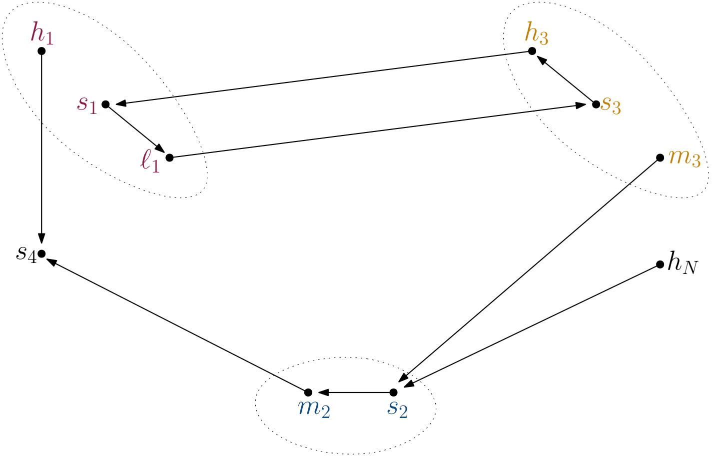
h_1	ℓ_1	m_2	h_3	m_3	h_N
s_4	~~s_2~~	s_4	s_1	s_2	s_2
s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

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



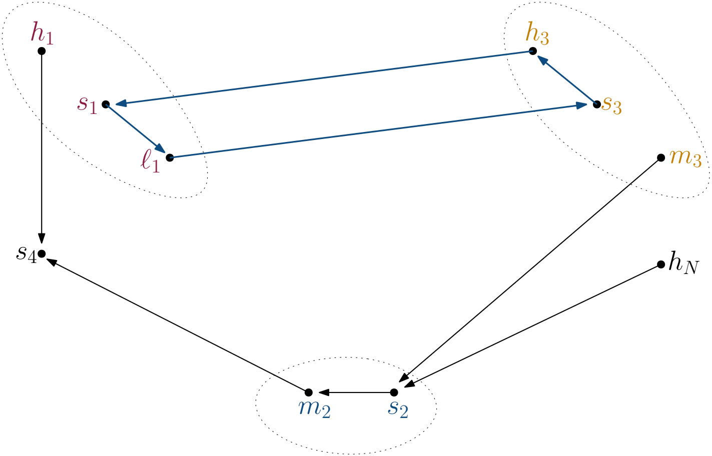
h_1	ℓ_1	m_2	h_3	m_3	h_N
$\underline{s_4}$	~~s_2~~	$\underline{s_4}$	$\underline{s_1}$	$\underline{s_2}$	$\underline{s_2}$
s_2	$\underline{s_3}$	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

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



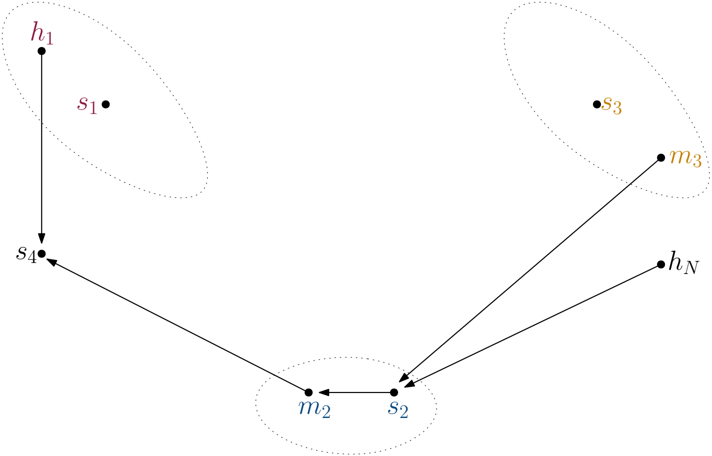
h_1	ℓ_1	m_2	h_3	m_3	h_N
$\underline{s_4}$	~~s_2~~	$\underline{s_4}$	$\underline{s_1}$	$\underline{s_2}$	$\underline{s_2}$
s_2	$\underline{s_3}$	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

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



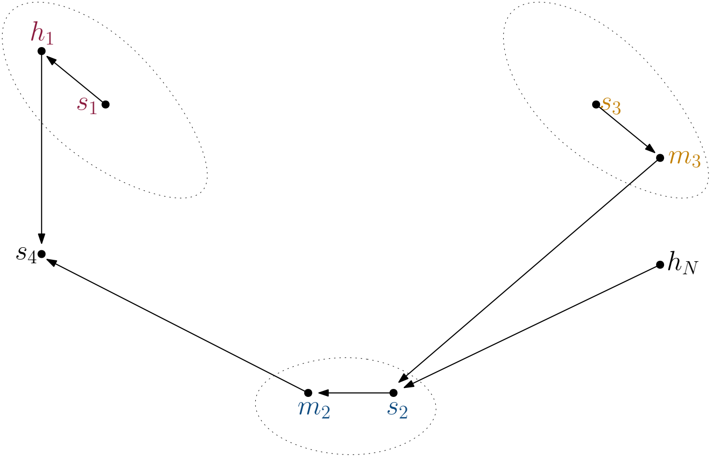
h_1	ℓ_1	m_2	h_3	m_3	h_N
s_4	~~s_2~~	s_4	s_1	s_2	s_2
s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

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



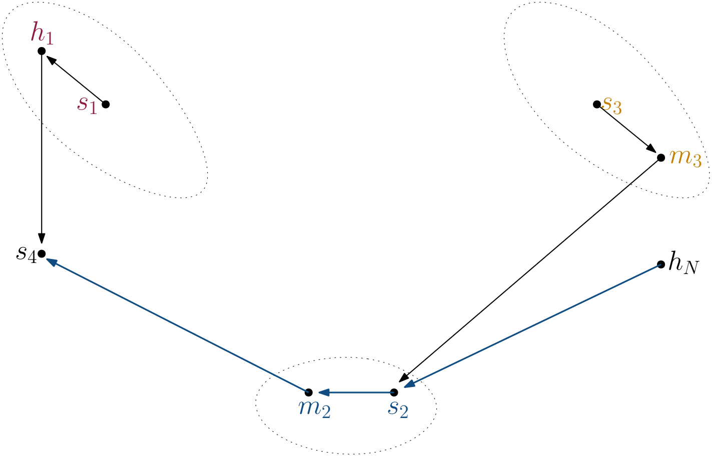
h_1	ℓ_1	m_2	h_3	m_3	h_N
$\underline{s_4}$	~~s_2~~	$\underline{s_4}$	s_1	$\underline{s_2}$	$\underline{s_2}$
s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

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



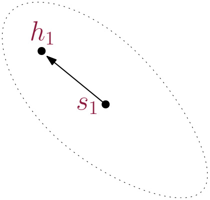
h_1	ℓ_1	m_2	h_3	m_3	h_N
$\underline{s_4}$	~~s_2~~	$\underline{s_4}$	s_1	$\underline{s_2}$	$\underline{s_2}$
s_2	s_3	s_3	s_3	s_1	s_1
s_3	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

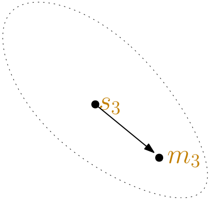
	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
	m	m	m	m
	ℓ	ℓ	h	h
status quo:	$\underline{h_1}, \ell_1$	$\underline{m_2}$	$\underline{m_3}, h_3$	$\emptyset$
current:	h_1, h_3	m_2	ℓ_1, m_3	$\emptyset$



h_1	ℓ_1	m_2	h_3	m_3	h_N
s_4	~~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

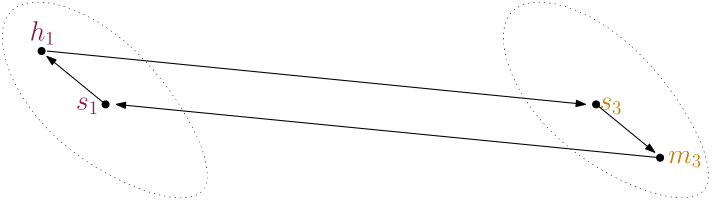
	s_1	s_2	s_3	s_4
	h	h	ℓ	ℓ
	m	m	m	m
	ℓ	ℓ	h	h
status quo:	$\underline{h_1}, \ell_1$	m_2	$\underline{m_3}, h_3$	$\emptyset$
current:	h_1, h_3	h_N	ℓ_1, m_3	m_2





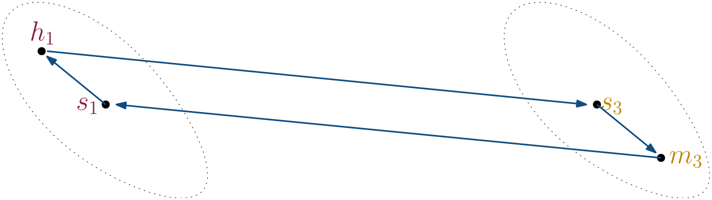
h_1	ℓ_1	m_2	h_3	m_3	h_N
s_4	~~s_2~~	s_4	s_1	s_2	s_2
s_2	s_3	s_3	s_3	$\underline{s_1}$	s_1
$\underline{s_3}$	s_1	s_2	s_1	s_3	s_3
s_1	s_4	s_1	s_4	s_4	s_4

	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	$\underline{m_3}, h_3$	$\emptyset$
current:	h_1, h_3	h_N	ℓ_1, m_3	m_2



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	$\underline{s_1}$	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	$\underline{m_3}, h_3$	$\emptyset$
current:	h_3, m_3	h_N	ℓ_1, h_1	m_2



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_3, m_3	h_N	ℓ_1, h_1	m_2

SI-CC Results

Theorem

For any given type ranking profile $\triangleright$, the induced SI-CC mechanism is strategy-proof and $\triangleright$-constrained efficient (i.e., among IR & $\triangleright$-SI matchings).

Remark

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

Type Ranking Design for Inequality Reduction

- Teacher types are assigned values in $\mathbb{R}_+$ such that

$$\theta_\emptyset = \theta_0 = 0 < \theta_1 < \ldots < \theta_{K-1}$$

  $\theta_\emptyset$: vacant seat type

  - Example: $\theta =$ years of experience

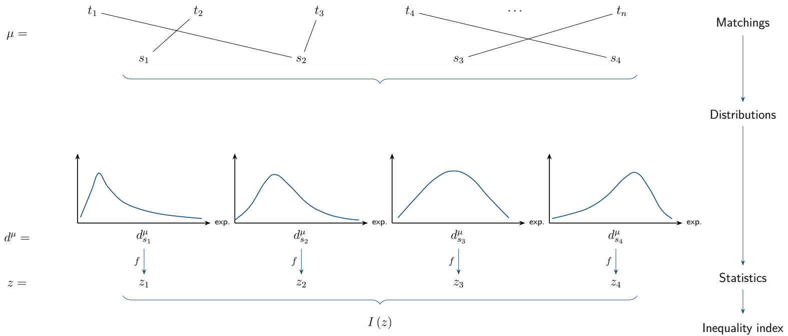
- Matching $\mu \Rightarrow$ type distribution $d^\mu = (d^\mu_s)_{s \in S}$
  $d^\mu_s = (d^{\mu,\theta}_s)_\theta$ so that $d^{\mu,\theta}_s$: # of type-θ teachers in μ_s

- Type distribution $d^\mu \Rightarrow$
  statistic vector for schools $f(d^\mu) = \Big(f(d^\mu_s)\Big)_{s \in S} \in \mathbb{R}^m$

  - Example: $f =$ average experience at a school
  - Property: f must be increasing with first-order stochastic dominance of distributions of types + continuous

- Statistic vector $f(d^\mu) \Rightarrow$ inequality index $I\big(f(d^\mu)\big) \in \mathbb{R}$

Type Ranking Design for Inequality Reduction



Type Ranking Design for Inequality Reduction

- Inequality index $I(z_1, \ldots, z_m)$

  Properties:

  - continuously differentiable almost everywhere
  - symmetric for schools with the same weight:
    w_s: ratio of the quota of school s to total quota of schools
  - satisfies a weak form of convexity:
    $\nearrow$ in the statistic of the worst school
    or
    $\searrow$ in the statistic of the best school

    $\Rightarrow$ $\searrow$ in inequality

Type Ranking Design for Inequality Reduction

- Examples:
  - Weighted Gini Index:

$$I(z) = \frac{1}{2\sum_s w_s z_s} \sum_s \sum_{s'} w_s w_{s'} |z_s - z_{s'}|$$

  - T20/B20 Ratio:

$$I(z) = \frac{\text{weighted average type of top 20\% of schools}}{\text{weighted average type of bottom 20\% of schools}}$$

- Matching μ reduces inequality below the status quo if

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

Large Market and Inequality Reduction

- Fix a (re)assignment market $\langle T, \Theta, S, q, P, \omega \rangle$, statistic f, and inequality index I.
- $E^n = \left(E_s^{\theta,n}\right)_{\theta \in \Theta, s \in S}$: sets of non-participating employees of each type for each school (indexed by n).

  $\Rightarrow$ Statistics are computed using all positions: participating teachers, non-participating teachers, and vacant seats.
- $\left|E_s^{\theta,n}\right| = n \times \left|E_s^{\theta,0}\right|$: $\#$ of non-participating employees of type θ in school s

  $\Rightarrow$ Base economy E_s^0 induces replica economies $\{E_s^n\}_{n=0}^{\infty}$.

  $\Rightarrow$ Sets of non-participating employees become dominant in the large.
  - Example: In France, 96.5% of teachers were non-participating in 2013.

Status-quo improvement $\Rightarrow$ Inequality reduction

Proposition

For any base economy for the replica economies, there exists a type ranking profile for schools $\triangleright^*$ *such that for a large enough market size* n*, if* μ *is* $\triangleright^*$*-status-quo improving then* μ *reduces inequality below the status quo.*

Sketch: Constructing the Type Ranking Profile $\triangleright^*$

- Let z^* be the vector of statistics computed in the limit economy ($\equiv$ statistics calculated with only non-participants)
- Partition the set of schools in two groups, L and H:
  - $s \in L$ if $\frac{\partial I}{\partial z_s}(z^*) \leq 0$
    $\Rightarrow$ Increasing the statistic for s decreases inequality
  - $s \in H$ if $\frac{\partial I}{\partial z_s}(z^*) > 0$
    $\Rightarrow$ Increasing the statistic for s increases inequality
- Type Ranking Design: Define type ranking profile $\triangleright^*$ as
  - For each school $s \in L$,

$$\theta_{K-1} \triangleright_s^* \theta_{K-2} \triangleright_s^* \ldots \triangleright_s^* \theta_1 \triangleright_s^* \theta_0 \triangleright_s^* \theta_\emptyset$$

    $\Rightarrow$ L schools rank high experience over low experience
  - For each school $s \in H$,

$$\theta_0 \triangleright_s^* \theta_\emptyset \triangleright_s^* \theta_1 \triangleright_s^* \theta_2 \triangleright_s^* \ldots \triangleright_s^* \theta_{K-1}$$

    $\Rightarrow$ H schools rank low experience over high experience

Sketch: Constructing the Type Ranking Profile $\rhd^*$

- We partitioned the set of schools in two groups as L and H as

  $s \in L$ if $\frac{\partial I}{\partial z_s}(z^*) \leq 0$:
  What if, for some other matching, increasing the statistic for some $s \in L$ increases the inequality?

  $s \in H$ if $\frac{\partial I}{\partial z_s}(z^*) > 0$:
  What if, for some other matching, decreasing the statistic for some $s \in H$ increases the inequality?

- Main problem: Generally, the signs of derivatives can change.
  $\Rightarrow$ Inequality index may increase with $\rhd^*$-status-quo improvement.

- Closing the proof: In a large market, the signs of partial derivatives do not change.

  $\Rightarrow$ Inequality index will decrease with status-quo improvement for $\rhd^*$.

Doing better than SI-CC?

- With a strictly FOSD-increasing statistic:

Proposition

There exists some base economy for the replica economies such that for n large enough, μ is $\triangleright^*$-status-quo improving only if μ reduces inequality below the status quo.

Proposition

No individually rational and strategy-proof mechanism generates less inequality whenever possible than the SI-CC mechanism induced by $\triangleright^*$.

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)...

- Unequal distribution of teachers across schools:

  Bobba et al. (2021); Bates et al. (2021); Biasi et al. (2021); Tincani (2021); Laverde et al. (2024) ...

Skip to the Conclusion

French Teacher Assignment

- Data on French centralized assignment of teachers to regions in 2013.
  - The current mechanism is employed in two stages, first for regional assignment and then for school assignment in each region.
  - We have robust regional data rather than assignment to individual schools.
  - The French Ministry of Education aims to decrease inter-regional inequality.
- Estimation of teachers' preferences over regions: $u_{t,R}$ Details
  - Separate estimation for tenured teachers and new teachers
  - Estimation on each of 8 fields (Math, History, Sports...)
- Final sample: 10,460 participating teachers: 5,833 tenured teachers (55.8%) and 4,627 new teachers.

Skip to the findings

Counterfactual Analysis

We aim to quantify mechanisms' performance in a real-life setting:

- SI-CC: SP and constrained efficient (among IR + SI mechanisms).
- Benchmark for SI-CC: TTC*
  - Similar to Abdulkadiroğlu and Sönmez (1999) TTC mechanism.
  - SP, Pareto efficient, IR, but not SI.
- Current French mechanism
  - Based on Gale and Shapley (1962) DA algorithm.
  - Ministry-mandated priorities of schools are used, mostly based on experience (with some exceptions).
  - Status-quo employees of a school are upgraded in priority only at that school above other teachers.
- Compromise between the current French mechanism and SI-CC: SI-CC*
  - New teachers' preferences are updated so that they rank the youngest regions first (in order of their submitted preferences)
  - SP, SI, and IR (as new teachers must rank all regions in France).

Teacher Types and Type Rankings of Regions

- Teacher type
  - Corresponds to her experience
  - We classify teachers into $K = 11$ experience bins

$$\theta_0 = 0 < \theta_1 < \ldots < \theta_{10}$$

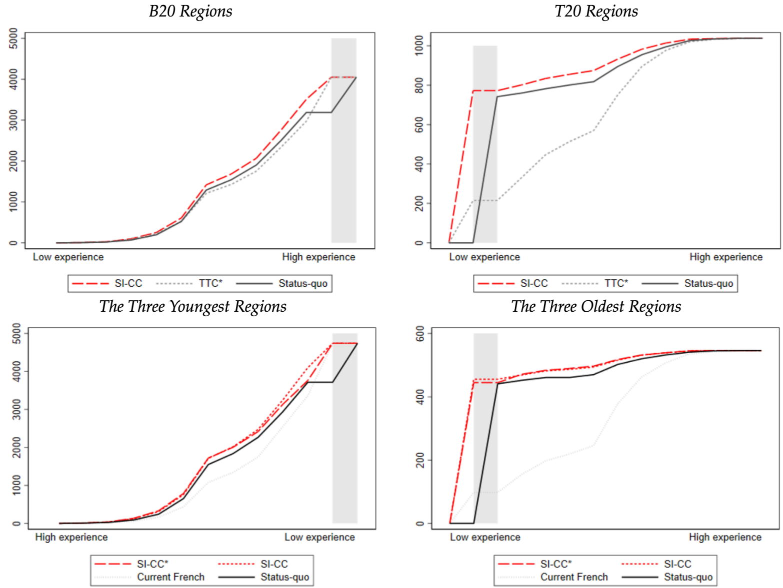
- Inequality index, Statistic, and type rankings of regions
  - We use the T20/B20 ratio inequality index and the mean experience statistic in each region: Sensitive to inequality at the extreme ends.
  - We use the type ranking profile $\rhd^*$ of T20/B20 ratio and mean experience based on participating and non-participating teachers.

	Regions	Type Ranking Profile $\rhd^*$
L = T20/B20 derivative < 0 or below median region	Créteil Versailles Amiens ...	$\theta_{10} \rhd_s^* \ldots \rhd_s^* \theta_1 \rhd_s^* \theta_0 \rhd_s^* \theta_\emptyset$
H = T20/B20 derivative > 0 or above median region	Bordeaux Rennes Lyon ...	$\theta_0 \rhd_s^* \theta_\emptyset \rhd_s^* \theta_1 \rhd_s^* \ldots \rhd_s^* \theta_{10}$

Empirical Results: SI-CC decreases inequality

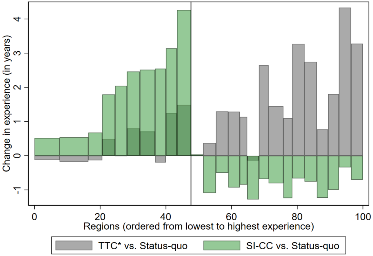
	SI-CC	TTC*	SI-CC*	Current French
	(1)	(2)	(3)	(4)
Panel A. Inequality Index				
T20/B20 ratio (at status quo = 1.3588)	1.3488	1.3691	1.3498	1.3829
Panel B. Teacher mobility				
Total moved/newly assigned	4,925	5,964	5,252	5,635
Tenured teachers moved from 3 oldest regions	74	106	72	56
Tenured teachers moved from 3 youngest regions	156	764	535	895
Tenured teachers moved from all regions	1,001	2,040	1,333	1,711
New teachers assigned	3,924	3,924	3,919	3,924
Ranks of tenured teacher assignments				
Rank $= 1$	298	940	344	675
Rank ≤ 2	1,032	1,926	1,145	1,515
Rank ≤ 3	1,504	2,417	1,641	1,980
Rank ≤ 4	1,874	2,729	2,027	2,332
Rank any	5,846	5,846	5,846	5,846
Ranks of new teacher assignments				
Rank $= 1$	811	370	682	315
Rank ≤ 2	1,177	594	969	511
Rank ≤ 3	1,430	767	1,154	671
Rank ≤ 4	1,632	912	1,300	814
Rank any	3,924	3,924	3,919	3,924

Empirical Results: SI-CC decreases inequality

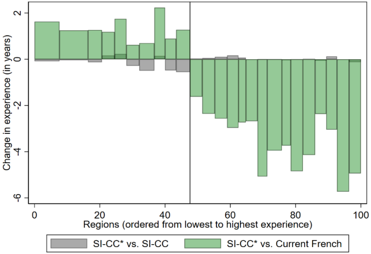


Empirical Results: SI-CC decreases inequality

(Re)assignment market



(Re)assignment market



Concluding Remarks

- We design schools' priorities that reflect a central authority's objective of reducing inequality.
    - School-specific priorities achieve an interlinked, global objective in a large market.
- We design a second-best mechanism, SI-CC, that improves both teachers' welfare and reduces inequality compared to an initial allocation.
- SI-CC can be used instead of the current French mechanism (a DA-variant based on reducing "justified envy").
    - In France, a TTC-variant mechanism is used for teacher assignment.
- Our counterfactual analysis using French data shows that
    - SI-CC reduces inequality across regions, unlike its benchmarks,
    - while ensuring a high teacher mobility (especially its variant, SI-CC*).

Appendix

Demand estimation

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

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

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

- Separate estimation for tenured teachers and newcomers
- Estimation on each of our 8 fields Details
- Final sample: 10,460 teachers: 5,833 tenured teachers (55.8%) and 4,627 new teachers

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 (2016), Akyol & Krishna (2017), Artemov, Che, & He (2019), Fack & Grenet & He (2019)
  - Teachers might skip unreachable regions from their ranking but
  - Assignment to the most preferred region within feasible regions
- Logit choice probabilities. Estimate β via ML.

Fit is a lot better than assuming truthtelling Back.

Eight markets

	Initially	Vacant		
	All teachers	Newcomers	assigned	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
% Married	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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