Statistical discrimination and affirmative action

Federico Echenique

Göteborgs Universitet, May 8 2019

Based on:

- *Statistical discrimination and affirmative action in the lab*, with A. Dianat (Esssex) and L. Yariv (Princeton)
- *A characterization of "Phelpsian" statistical discrimination*, with C. Chambers (Georgetown).

Discrimination (O.E.D.)

Unjust or prejudicial treatment of a person or group, esp. on the grounds of race, gender, sexual orientation, etc.; frequently with against.

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Diskriminering (Sv. Akademien's Ordbok)
orättvis behandling av viss (minoritets)grupp

Discrimination

- Taste-based discrimination (Becker (1957))
- Statistical discrimination (Phelps (1972); Arrow (1973))

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- Statistical discrimination (Phelps (1972); Arrow (1973))

In the absence of direct information about a certain aspect of ability, a decision-maker would substitute group averages or variances corresponding to the individual's demographics (gender, race, etc.)

- Phelpsian: informational content of type-specific signal structures.
- Arrowian: Self-fulfilling stereotypes.

Affirmative Action

In 1961, a JFK Executive Order requires contractors "take affirmative action to ensure that applicants are employed, and employees are treated during employment, without regard to their race, creed, color, or national origin."

In 2003 (Grutter v. Bollinger), Sandra Day O'Connor: "We expect that 25 years from now, the use of racial preferences will no longer be necessary to further the interest (in student-body diversity) approved today."

Not only the US:

- Australia
- Brazil
- Canada
- China
- India
- Pakistan

Source: T. Sowell.

- Sri Lanka
- Soviet Union
- U. K.
- Malaysia
- New Zealand
- Nigeria

Statistical discrimination and affirmative action in the lab

(with A. Dianat and L. Yariv)

Statistical discrimination

With field data it is very hard to test for statistical discrimination, and to rule out taste-based.

Hence, lab experiments.

Statistical discrimination

Our study:

- Can we induce statistical discrimination in the lab?
- Once induced, can affirmative action get rid of it?

Statistical Discrimination and Multiple Equilibria

	Hire	Not Hire
Invest	$1800 - c, 1600$	$1000 - c, 1200$
Not Invest	$1400, 400$	$1200, 1200$

- $c =$ cost of investment
- If $c \leq 400$, there are two pure-strategy Nash equilibria:
    1. (Invest, Hire)
    2. (Not Invest, Not Hire)

Two kinds of workers

- **GREEN**
- **PURPLE**

What We Do

- Induce “genuine” discrimination in the lab
- Then lift the asymmetry between **GREEN** and **PURPLE** workers
  - Will discrimination persist? Meaning, will we observe *statistical* discrimination?
- Introduce affirmative action
  - Will discrimination vanish?
- Remove affirmative action
  - Are the effects long-lasting?

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Seed Stage (10 rounds)

	Hire	Not Hire
Invest	$1800 - c, 1600$	$1000 - c, 1200$
Not Invest	$1400, 400$	$1200, 1200$

- **GREEN** workers: $c = 200$
- **PURPLE** workers: $c = 600$

Baseline Stage (10 rounds)

	Hire	Not Hire
Invest	$1800 - c, 1600$	$1000 - c, 1200$
Not Invest	$1400, 400$	$1200, 1200$

- **ALL workers:** $c = 200$
- **Workers:** Invest if $p_{Hire} \geq \frac{2}{3}$
- **Firms:** Hire if $p_{Invest} \geq \frac{2}{3}$

Stage 3: Introducing Affirmative Action

	Hire	Not Hire
Invest	$1600, 1600 + s$	$800, 1200$
Not Invest	$1400, 400 + s$	$1200, 1200$

- All workers: $c = 200$
- Affirmative action policy: subsidy s for hiring a **PURPLE** worker

Stage 3: Introducing Affirmative Action

	Hire	Not Hire
Invest	$1600, 1600 + s$	$800, 1200$
Not Invest	$1400, 400 + s$	$1200, 1200$

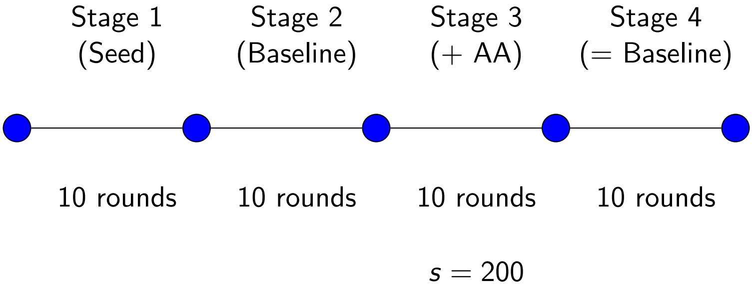
- All workers: $c = 200$
- Affirmative action policy: subsidy s for hiring a **PURPLE** worker
- Three treatments:
  1. **Subsidy**: $s = 200$ for 10 rounds
  2. **High Subsidy**: $s = 900$ for 10 rounds
  3. **Long Subsidy**: $s = 200$ for 20 rounds

Stage 4: Removing Affirmative Action (10 rounds)

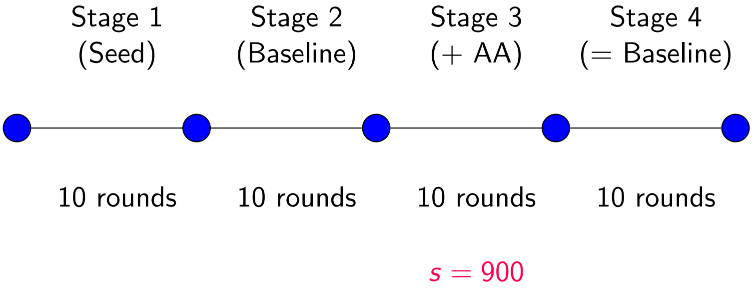
	Hire	Not Hire
Invest	$1600, 1600$	$800, 1200$
Not Invest	$1400, 400$	$1200, 1200$

- All workers: $c = 200$
- Same game as baseline (Stage 2).

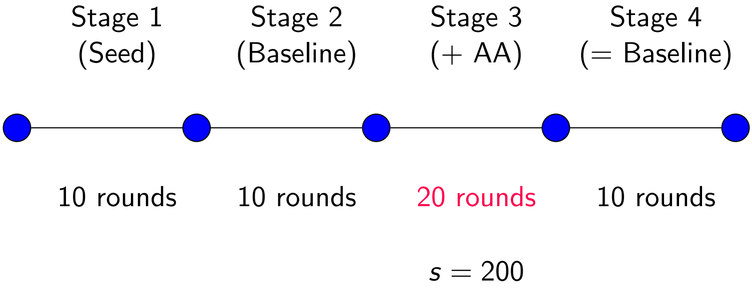
Subsidy Treatment



High Subsidy Treatment



Long Subsidy Treatment



Implementation

- Experimental Social Science Laboratory (ESSL) at UC Irvine using the oTree software (Chen, Schonger, and Wickens 2016)
- 15 sessions, 268 subjects.
- Roles and colors fixed throughout session.
- 1/40 (1/50) experimental rounds and 1/2 risk tasks were randomly selected for subject payment (+$7 show-up payment)

Worker Interface

Stage 1: Round 1

You are a GREEN worker

GREEN workers have an investment cost of 200 (c = 200)

PURPLE workers have an investment cost of 600 (c = 600)

	Hire	Not Hire
Invest	1800 - c, 1600	1000 - c, 1200
Not Invest	1400, 400	1200,1200

	Avg. Investment Rate	Avg. Hiring Rate
GREEN worker	0.0	0.0
PURPLE worker	0.0	0.0

Do you wish to invest in training?

- Yes
- No

In your view, what is the likelihood that the firm you are paired with chose to hire you?

-1

Next

Stage 1: Round 1

You are a firm

You are paired with a GREEN worker

GREEN workers have an investment cost of 200 (c = 200)

PURPLE workers have an investment cost of 600 (c = 600)

	Hire	Not Hire
Invest	1800 - c, 1600	1000 - c, 1200
Not Invest	1400, 400	1200,1200

	Avg. Investment Rate	Avg. Hiring Rate
GREEN worker	0.0	0.0
PURPLE worker	0.0	0.0

Do you wish to hire the worker?

- **Yes**
- **No**

In your view, what is the likelihood that the worker you are paired with chose to invest in training?

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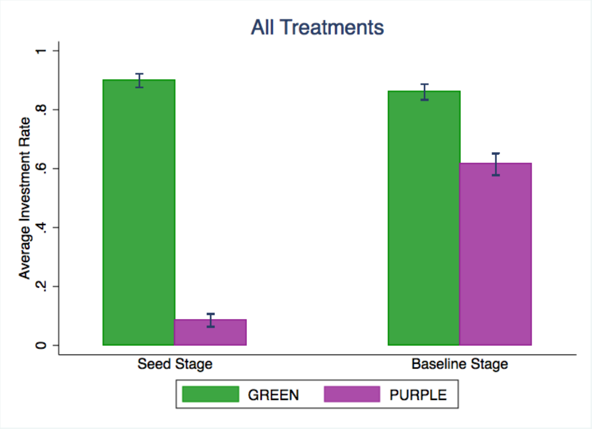
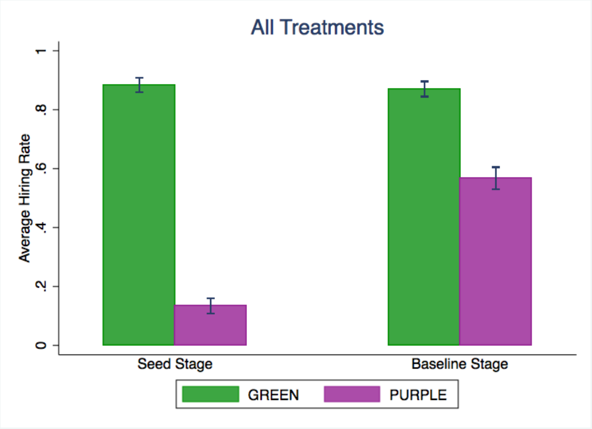
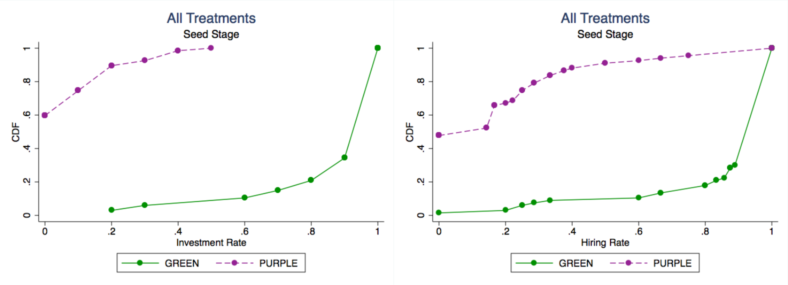
Stages 1-2: Workers



Stages 1-2: Firms

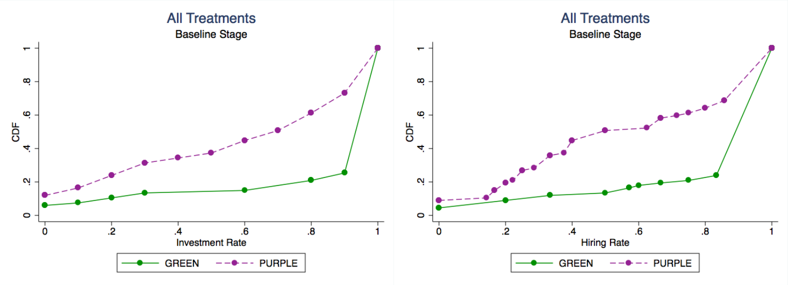


Subject-Level CDFs: Seed (Stage 1)



- We reject the null hypothesis that investment and hiring rates for **GREEN** and **PURPLE** workers come from the same distribution (Kolmogorov-Smirnov test, $p < 0.001$).

Subject-Level CDFs: Baseline (Stage 2)



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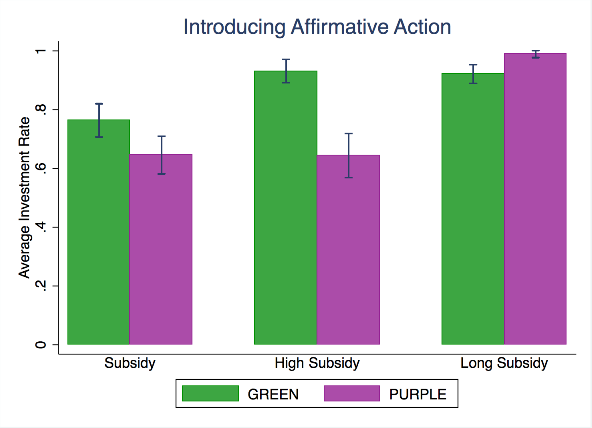
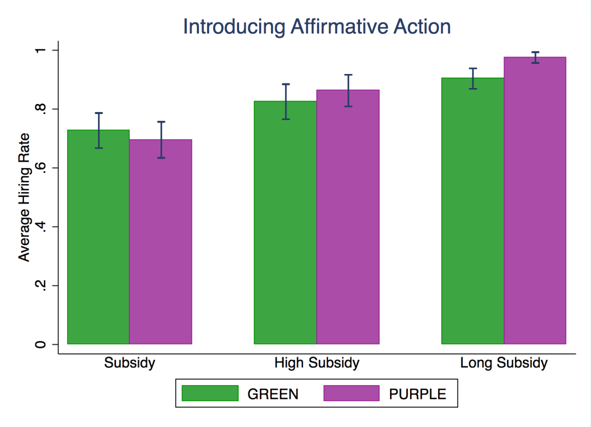


- **Subsidy** & **High Subsidy**: PURPLE workers invest at a significantly lower rate than **GREEN** workers (two-sided t-test, $p = 0.007$ for Subsidy, $p < 0.001$ for High Subsidy).
- **Long Subsidy**: PURPLE workers invest at a significantly higher rate than **GREEN** workers (two-sided t-test, $p < 0.001$).

Stage 3 (AA): Firms



- **Subsidy** & **High Subsidy**: Firms hire **GREEN** and **PURPLE** workers at the same rate (two-sided t-test, $p = 0.463$ for Subsidy, $p = 0.357$ for High Subsidy).
- **Long Subsidy**: Firms hire **PURPLE** workers at a significantly higher rate than **GREEN** workers (two-sided t-test, $p < 0.001$).

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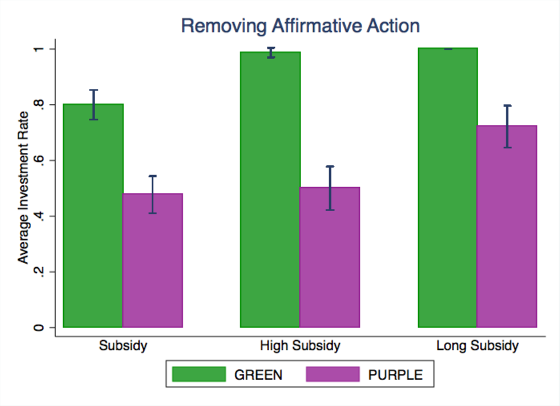
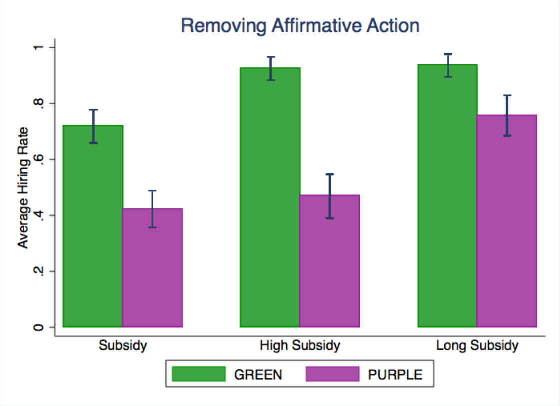
Removing AA (Stage 4 = Baseline): Workers



- **All treatments**: **PURPLE** workers invest at a significantly lower rate than **GREEN** workers (two-sided t-test, $p < 0.001$ for all treatments).

Removing AA (Stage 4 = Baseline): Firms



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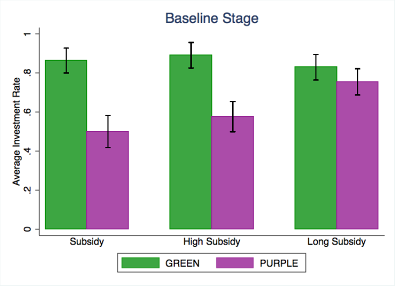
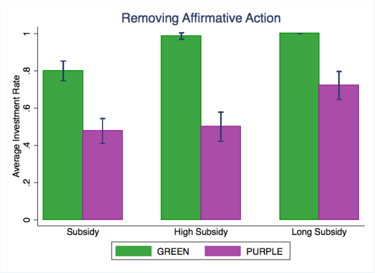
Comparing stages 2 and 4 (workers)





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Beliefs

	Seed Stage	Baseline Stage	Introducing AA	Removing AA
Subsidy	0.00	0.05	0.48	0.07
High Subsidy	0.05	0.07	1.00	0.21
Long Subsidy	0.06	0.17	0.90	0.40

Table: Fraction of firms hiring a **PURPLE** worker over a **GREEN** worker

Worker Belief and Public History

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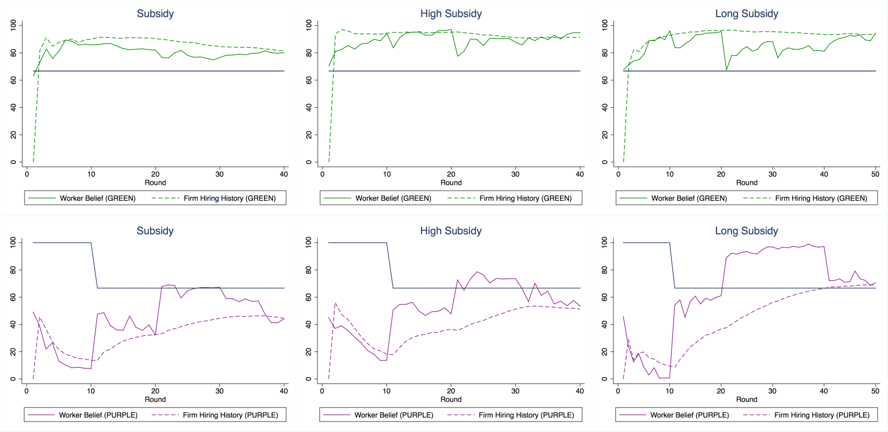
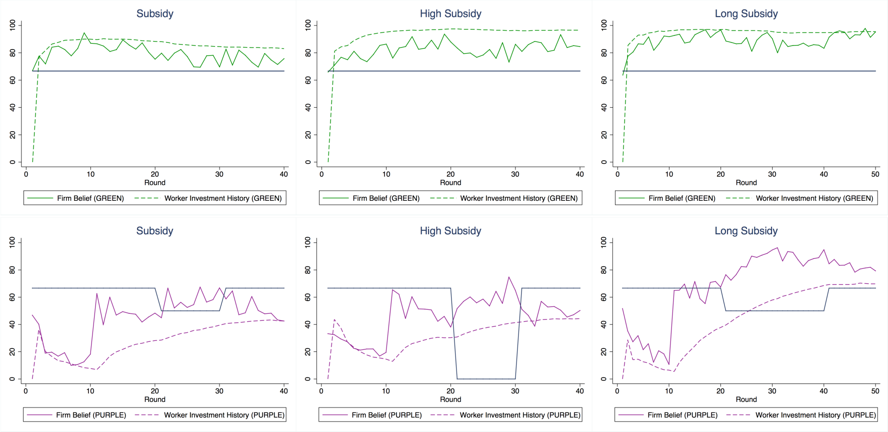


Firm Belief and Public History



Caveats

- Our results suggest that longer affirmative action policies might be effective
  (and field data literature points to AA policies lasting longer than planned).
- AA may be effective remedy to taste-based discrimination. Exposure to people who are different may reduce bias.
- Dynamic effects.

A characterization of “Phelpsian” statistical discrimination

with Chris Chambers (Georgetown).

Phelpsian statistical discrimination

- Phelps (1972): informational content of population of signal distributions.
- (at least as explained by Aigner and Cain (1977)

Idea

- A worker and a firm

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- Worker is paid its contribution to the firm
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- The worker belongs to a population that generates signals according to a distrbution π.

Profit for firm A from worker with signal s is

$$V_A(s) = \max_{a \in A} E_s(a(\tilde{\theta}))$$

Idea

- Situation is *non-discriminatory* if for all π, π' and firms A, $E_\pi(p) = E_{\pi'}(p)$ implies that

$$E_\pi V_A(\tilde{s}) \neq E_\pi V_A(\tilde{s}).$$

- Distributions are *identified* if $E_\pi(p) = E_{\pi'}(p)$ implies that $\pi = \pi'$.

Idea

Theorem:
Non-discriminatory $\Leftrightarrow$ Identified $\Leftrightarrow$ Fair "skills-based" remunerations.

The model

$\mathcal{T} \subseteq \Delta(\Theta)$ a set of *types*

for $s \in \mathcal{T}$,

$$v_A(s) \equiv \max_{a \in A} \sum_{\theta \in \Theta} a(\theta) s(\theta).$$

Population

A *population* is a distribution $\pi \in \Delta(\mathcal{T})$ over types.

$\mathcal{T}$ is *non-discriminatory* if for any $\pi, \pi' \in \Delta(\mathcal{T})$, and $A \subseteq \mathbf{R}^{\Theta}$, if $p_\pi = p_{\pi'}$, then

$$\int_{\mathcal{T}} v_A(t) d\pi(t) = \int_{\mathcal{T}} v_A(t) d\pi'(t).$$

Example

Let $\Theta = \{\theta_1, \theta_2, \theta_3\}$, and

$$\mathcal{T} = \{(1,0,0),(1/2,1/2,0),(0,1/2,1/2),(0,0,1)\}$$

$A = \{(1,0,0),(0,1/2,3)\}$

	$t=(1,0,0)$	$t=(1/2,1/2,0)$	$t=(0,1/2,1/2)$	$t=(0,0,1)$
$\pi(t)$	$1/3$	0	$2/3$	0
$\pi'(t)$	0	$2/3$	0	$1/3$
$v_A(t)$	1	$1/2$	$7/4$	3

Observe that $p_\pi = p_{\pi'} = (1/3,1/3,1/3)$.

Proposition

For any $\mathcal{T}$ and any set of actions A, if $\pi, \pi' \in \Delta(\mathcal{T})$ for which $p_\pi \neq p_{\pi'}$, then there is k for which

$$\int_T v_{A+k}(t) d\pi(t) \neq \int_T v_{A+k}(t) d\pi'(t).$$

We say that $\mathcal{T}$

- is *identified* if for any $\pi, \pi' \in \Delta(\mathcal{T})$, if $p_\pi = p_{\pi'}$, then $\pi = \pi'$;
- *admits fair valuations* if for any finite subset $A \subseteq \mathbf{R}^\Theta$, there is $\alpha_A \in \mathbf{R}^\Theta$ for which for all $t \in \mathcal{T}$,

$$v_A(t) = \sum_\theta \alpha_A(\theta) t(\theta).$$

- *admits fair valuations for binary sets* if for any binary subset $A \subseteq \mathbf{R}^\Theta$, there is $\alpha_A \in \mathbf{R}^\Theta$ for which for all $t \in \mathcal{T}$, $v_A(t) = \sum_\theta \alpha_A(\theta) t(\theta)$.

Theorem

The following are equivalent.

1. $\mathcal{T}$ *is non-discriminatory.*
2. $\mathcal{T}$ *is non-discriminatory for binary sets.*
3. $\mathcal{T}$ *is identified.*
4. $\mathcal{T}$ *admits fair valuations.*
5. $\mathcal{T}$ *admits fair valuations for binary sets.*

Proposition

If $\mathcal{T}$ admits fair valuations, then for each finite $A \subseteq \mathbf{R}^{\Theta}$ and corresponding $\alpha_A \in \mathbf{R}^{\Theta}$, we have for every $s^* \in \mathcal{T}$:

$$\sum_{\theta} \alpha_A(\theta) s^*(\theta) = \inf\{\sum_{\theta} y(\theta) s^*(\theta) : y \in \mathbf{R}^{\Theta}$$
$$v_A(s) \leq \sum_{\theta} y(\theta) s(\theta) \forall s \in \mathcal{T}\}.$$

Let $W_A : T \to \mathbf{R}$ be

$$W_A(s) \equiv \max\{\int_T v_A(\tilde{s}) d\pi(\tilde{s}) : \pi \in \Delta(T) \text{ and } s = \int_T \tilde{s} d\pi(\tilde{s})\}.$$

Corollary

For any $\mathcal{T}$, ∂T is non-discriminatory iff for every A, W_A is affine (linear).[1]

[1] Because the domain of W_A is a set of probability measures, W_A is linear if it is affine. In fact, in this case we have $W_A(s) = \sum_{\theta \in \Theta} \alpha_A(\theta) s(\theta)$, where α_A is as in Proposition 2.