The Limits of Color-Blind Affirmative Action Policies

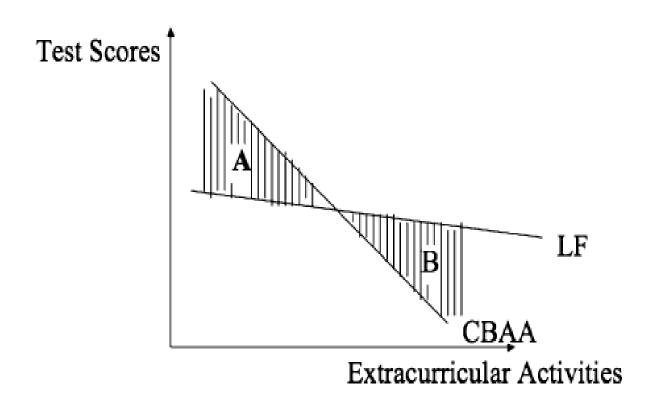
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Affirmative Action without Explicit Racial Discrimination

 Color-blind (non-racially discriminatory) affirmative action exploits statistical associations in the population between an applicant's racial identity and his/her non-racial traits
 [Texas 10% Plan famously illustrates the non-transparency]

- A policymaker alters the weight given to non-racial traits for all applicants in such a way as to increase the yield in selection process from a targeted group.
- One consequence of this kind of policy is that selection efficiency must in general be reduced for all applicants. Policy can't be 'conditionally' (within group) meritocratic.

An Illustrative Example of Color-Blind Affirmative Action



Students in area A are excluded, and in area B are included, by the policy. There are more disadvantaged group students to be found in area B than in area A.

Use Data to Estimate (presumed) Linear Relationships

Academic Performance Equation:

$$p_i = [\text{Expected performance } | x_i] = \beta \cdot x_i = \sum_{i \in J} \beta_i x_i^j$$

Racial Identity Equation [prob {applicant in targeted group}]:

$$r_i \equiv \Pr[R_i = 2 \mid x_i] = \gamma \cdot x_i = \sum_{j \in J} \gamma_j x_i^j$$

Finding an Optimal Policy: The Planner's Problem

$$\max_{[A_i]_{i\in I}} \left\{ \left(\frac{1}{c}\right) \sum_{i\in I} A_i p_i \right\}, \quad \text{subject to the following three constraints:}$$

$$(\mathrm{i}) \ A_i \in [0,1], \ i \in I, \quad (\mathrm{ii}) \ \frac{1}{|I|} \Biggl\{ \sum_{i \in I} A_i \Biggr\} \leq c, \quad (\mathrm{iii}) \ \frac{1}{|I|} \Biggl\{ \sum_{i \in I} A_i r_i \Biggr\} \geq r.$$

Laissez-Faire Solution: Threshold Rule on Predicted Performance

$$A_i^* = \begin{cases} 1 & \text{if } \beta \cdot x_i > \mu \\ 0 & \text{if } \beta \cdot x_i < \mu. \end{cases}$$

Here μ must be chosen in such a way that constraint (ii) holds with equality.

Color-Sighted Affirmative Action Solution: Race-Specific Thresholds

Under the CS regime, there will be separate thresholds for the racial groups So, for a pair of numbers μ_1 and μ_2 , with $\mu_1 > \mu_2$, we have:

$$A_i^* = \begin{cases} 1 & \text{if } \beta \cdot x_i > \mu_{R_i} \\ 0 & \text{if } \beta \cdot x_i < \mu_{R_i}. \end{cases}$$

Here the μ_1 and μ_2 are to be chosen such that selection rates for the two groups are consistent with the capacity and representation constraints holding as equalities.

Color-Blind Affirmative Action: Modified weights in scoring equation

Under the CB regime, a Lagrangian multiplier on constraint (iii) alters the admissions policy relative to LF because nonracial traits are now to be valued both for their association with prospective academic performance and for their ability to predict an applicant's race. Thus, the optimal CB policy is characterized by two numbers θ and μ' such that:

$$A_i^* = \begin{cases} 1 & \text{if } [\beta + \theta \gamma] \cdot x_i > \mu' \\ 0 & \text{if } [\beta + \theta \gamma] \cdot x_i < \mu', \end{cases}$$

where μ' and θ are such that constraints (ii) and (iii) above hold as equalities.

activities and test scores). Under LF and CS regimes, the college's marginal rate of substitution between traits j and k as reflected in the admissions policy function, denoted by $MRS_{j,k}$, is equal to the relative importance of these traits in forecasting student performance:

$$MRS_{j,k} = \frac{\beta_j}{\beta_k},$$

whereas, under the CB regime, the rate of substitution between traits j and k that holds constant the probability of being admitted is given by:

$$MRS_{j,k} = \frac{\beta_j + \theta \gamma_j}{\beta_k + \theta \gamma_k}.$$

Table 3. Performance Equation: Predicted College Rank

	College A	College B	College C	College D	
SAT math	4.04 (1.39)	-0.60 (1.78)	5.08 (1.69)	7.57 (1.51)	
SAT verbal	5.47 (1.31)	8.98 (1.62)	7.15 (1.68)	12.85 (1.30)	
HS percentile	3.12 (1.11)	8.79 (1.42)	8.42 (1.84)	7.49 (1.79)	
Mother college educated	2.58 (2.63)	8.40 (3.00)	-3.45(3.76)	3.61 (2.15)	
Father college educated	4.35 (2.99)	-3.76 (3.60)	6.07 (4.04)	5.48 (2.84)	
Zip income	-0.04(0.64)	-1.44(0.80)	-0.47(0.72)	-0.74(0.44)	
Legacy	4.66 (4.55)	0.59 (4.05)	0.65 (3.64)	-0.47 (1.96)	-
Percent Asian in zip	14.07 (16.83)	16.78 (16.82)	6.28 (19.45)	33.05 (13.58)	:
Percent Black in zip	-11.72 (5.78)	-29.10 (10.99)	-14.26 (7.59)	-15.91 (5.31)	-
Percent Hispanic in zip	-15.76 (11.21)	-22.15 (11.51)	-0.42(11.40)	-3.24(9.10)	
Male	-4.77(2.06)	n/a	n/a	-7.92(1.66)	_
R^2	0.16	0.21	0.19	0.37	
Number of observation	761	429	512	494	

College rank is percentiles in distribution of cumulative GPA among students who matriculated at that college in 1989. HS percentile is studen dummies for students' mother and father being college educated. Zip income is the median income of the student's zip code from the 1990 Ce percentile 10 percentiles, ZIP income \$10,000. We used dummies for the missing data. (Coefficients for these variables are not reported in

Table 4. Race Equation: Probability of Being Black

	College A	College B	College C	College D
SAT math	-0.06 (0.01)	-0.06 (0.01)	-0.07 (0.01)	-0.10 (0.02)
SAT verbal	-0.02 (0.01)	-0.03(0.01)	-0.06 (0.01)	-0.04 (0.01)
HS percentile	-0.04 (0.01)	0.01 (0.01)	-0.07 (0.01)	-0.05 (0.01)
Mother college educated	0.02 (0.02)	0.01 (0.02)	0.03 (0.03)	0.01 (0.02)
Father college educated	-0.11 (0.02)	-0.04 (0.02)	-0.08(0.03)	-0.02 (0.03)
Zip income	0.01 (0)	0.01 (0.01)	0 (0.01)	0.01 (0.01)
Legacy	0.01 (0.03)	-0.02(0.03)	-0.01 (0.03)	-0.09 (0.03)
Percent Asian in zip	-0.25 (0.12)	-0.06(0.11)	-0.10(0.15)	0.14 (0.20)
Percent Black in zip	0.57 (0.04)	0.57 (0.07)	0.85 (0.06)	0.57 (0.06)
Percent Hispanic in zip	-0.02(0.08)	-0.02(0.08)	-0.08(0.09)	-0.13(0.12)
Male	0.01 (0.02)	n/a	n/a	0.01 (0.02)
R^2	0.41	0.22	0.55	0.37
Number of observations	761	429	512	494

Dependent variable is student's probability of being black. HS percentile is students' percentile in his high school. Mother's and father's educated. Zip income is the average income of the student's zip code from the 1990 Census; n/a, not available. Increments: SAT variables 100 dummies for the missing data. (Coefficients for these variables are not reported in this table.)

Table 7. Weight on Students' Characteristics in the Admission Formula for Laissez-Faire and Color-Blind Policies,

	SAT	math	SAT verbal		HS SAT verbal percent			Mother educated		Father educated		Income		Percer black	
	LF	СВ	LF	CB	LF	СВ	LF	СВ	LF	СВ	LF	СВ	LF		
College A	4.04	0.16	5.47	4.18	3.12	0.53	2.58	3.87	4.35	-2.76	-0.04	0.61	-11.72	2	
College B	-0.60	-4.88	8.98	6.84	8.79	9.50	8.40	9.11	-3.76	-6.61	-1.44	-0.73	-29.10	1	
College C	5.08	1.68	7.15	4.24	8.42	5.02	-3.45	-1.99	6.07	2.18	-0.47	-0.47	-14.26	2	
College D	7.57	-3.74	12.85	8.33	7.49	1.83	3.61	4.74	5.48	3.22	-0.74	0.39	-15.91	1	

Table 5. Relative Performances of Color-Blind and Color-Sighted Policies, by Race Constraint

	College A	College B	College C	College D	College E	College F	College G	Average
Random admissions	86.29	87.22	80.43	85.04	80.67	85.62	81.26	83.62
Laissez-faire without SAT	96.96	98.50	97.00	93.90	95.01	98.45	96.65	96.88
Laissez-faire without HS percentile	99.77	98.02	97.89	99.58	99.56	98.67	97.24	98.57
Color sighted Color blind	97.97 94.28	99.55 98.67	97.64 95.33	97.43 90.82	98.66 96.40	98.59 95.95	99.77 98.74	98.68 96.16

Predicted college rank of a student is estimated by the OLS regression. For each policy, we compute the average predicted college rank of the admitted class. We call this value the performance of the policy. To compute the relative performance, we index laissez-faire's performance as 100. For example, color-sighted relative performance = (color-sighted performance × 100)/(laissez-faire performance). Average is the population-weighted average.

