Research Memorandum on “Color-Blind Affirmative Action”

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I. Introduction

This memorandum describes the research strategy being pursued and reports on preliminary results obtained in the “Color-Blind Affirmative Action” project supported by the Andrew W. Mellon Foundation at the Institute on Race and Social Division at Boston University. This project employs economic analysis to develop a conceptual framework for understanding the consequences likely to ensue from the use of so-called “race neutral alternatives” to conventional racial affirmative action policies in college admissions. As elaborated below, in comparison to conventional, race-conscious affirmative action, such race-neutral alternatives could have a significant, unintended deleterious impact on the efficiency of the student selection process. Our study also develops and applies techniques that provide plausible quantitative estimates of the likely magnitudes involved.

II. Background Discussion

The legal and political climate has shifted dramatically over the last decade on the issue of racial affirmative action. Accordingly, a number of institutions (particularly in higher education) have begun to reformulate their policies. Texas and Florida, for instance, have guaranteed admission to the public university system for all high school students in the state graduating in the top ten and twenty percent, respectively, of their senior classes. Some private institutions (e.g., Mount Holyoke College) have eliminated reporting SAT or ACT scores as a condition of application. Public officials in California have speculated openly about doing away with the requirement that applicants to the state's university system submit standardized test scores. Some scholars and analysts have urged elite institutions to rely more on the socioeconomic background of applicants and other non-academic characteristics when assessing their suitability for admission.

Many justifications can be offered for such changes, but a primary factor would seem to be a desire to promote diversity without using explicit racial preferences. For this reason, we call these kinds of admissions policies "color-blind affirmative action," to be contrasted with conventional, ``color-sighted" policy. Some economic implications of this emergent practice are explored in this paper. There are two aspects of the investigation.

In the first place, as a purely statistical matter the fact that some non-racial traits may be distributed differently within racial groups allows selectors to generate diversity without engaging in explicit discrimination by employing proxies, thereby altering the perceived trade-off among variables in a selection formula. For instance, it is plausible to suppose that, absent any concerns about racial representation, the relative weight given to high school grades versus aptitude test scores would be determined by the respective correlations of these variables with a student's post-admissions performance. But once racial preferences are abandoned, should the institution desire to maintain diversity, the fact that the distribution of grades within racial groups is much more similar than is the distribution of test scores means that, by raising the weight given to grades in the selection process (as Texas and Florida have done,) an institution can raise the representation of the disadvantaged racial group.

In the empirical part of our paper we illustrate the potential for using race proxies in this way by analyzing hypothetical college admissions problems, using data from the College and Beyond Survey, on which the analysis in the widely discussed study of affirmative action in higher education, *The Shape of the River* (Bowen and Bok, 1998), was based. We use actual student profiles from the matriculating classes (entering college in 1989) of seven selective institutions (three research universities and four liberal arts colleges, labeled “College A” through “College G” in what follows so as to maintain institutional anonymity). We conduct imaginary admissions exercises, in effect supposing that the colleges in question would have had to admit only half as many students as were, in fact, admitted. Their selection problem is to choose which half of the students to retain from among the actual matriculates. Their representation goal is to maintain the original proportion of black students in this reduced class. They pursue this goal with policies that are either color-sighted (i.e., racially preferential) or color-blind (i.e., using proxies for race). We demonstrate that the optimal color-blind affirmative action policy can be represented as the solution to a simple linear programming problem, derive the optimal admissions policies, and examine how the use of color-blind affirmative action alters the relative weight given to non-racial traits in a college's admissions formula. Compared to admissions policy that is unconcerned with racial representation, the optimal color-blind affirmative action policy gives less weight to academic factors and more weight to social background factors in the selection formula. Moreover, our simulations imply that such policy is significantly less effective than conventional, color-sighted affirmative action at screening for the better academic prospects, given the same racial representation target.

III. Some Theoretical Issues

[A reader mainly interested in our numerical results may skip this section without loss.]

It is important to note that changing the weight given various acquired traits (like grades and test scores) in an admissions formula will alter the incentives that applicants face as they enter the competitive selection process. In general, "color-blind affirmative action" exploits the difference across racial populations in the distribution of productivity-related traits in order to ``bias" the selection formula toward a greater yield from the disadvantaged group. However, economic theory suggests that pursuing racial diversity via such indirect means may be particularly inefficient.

To see why, consider an extreme example: one way to achieve population proportionality for all groups is to select from among candidates for a limited number of positions at random, with every applicant facing the same chance of success. This assures (with large numbers of applicants and statistical independence of applicant traits) that the fraction of successful candidates from any group equals the fraction of applicants from that group. Yet, random selection leaves applicants without an incentive to acquire traits valued by the selector. In equilibrium, the population of applicants (from all groups) will be much less distinguished under random selection, despite the fact that those selected will indeed be racially diverse. Theoretical analysis in this paper shows that the intuition of this extreme example holds in the general case: The most efficient way to promote racial diversity in the presence of large group differences in the distribution of productive traits is through the use of racially preferential policy. (We realize, of course, that efficiency is not the only consideration when assessing the desirability of such policy.)

Note well: there is a fundamental externality here. Individual selectors will not take account of how their choice of selection criteria affects the distribution of traits in a population of applicants. And yet, when all selectors use a particular method of ranking applicants -- in the extreme example, ranking them randomly -- this practice undermines the incentive all applicants have to acquire traits valued by the selectors. Thus, random selection will not look to any one selector to be as bad as it really is. In equilibrium under random selection, the population of applicants -- having no incentive to acquire valued traits -- will be undistinguished. This makes the adoption of a random selection method look like a low cost move for any given selector. But when all selectors make this move, they are all very much worse-off than they would be if none of them made it. What we are able to show in our theoretical analysis is that the intuition of this extreme example carries over to the general case.

Thus, in the theoretical part of the paper (not reported on here) we develop a model in which applicants are randomly matched with a competitor belonging to one of two racially defined subgroups of a population, for a pair-wise contest for some position that only one of them can attain. Workers prepare for this competition by exerting effort prior to knowing against whom they will be matched. The two racial groups differ in the distribution of effort cost (ability) among their members, with one group being "disadvantaged" relative to the other. Contest evaluators, who are concerned to reward the highest effort possible, observe preparatory effort. But they are also concerned to attain some specified degree of racial representation amongst winners, on the average. To pursue this representational goal, affirmative action may come to bear in evaluating the pair-wise contests. Given this set-up, "race-sighted" affirmative action takes the form of giving contestants from the disadvantaged racial group a ``handicap" in the effort competition when they face opponents from the advantaged group. Race-blind affirmative action takes the form of deciding certain ``close" contests between any two workers by flipping a coin. The incentives to exert preparatory effort are affected by affirmative action, and affected differently depending on how the affirmative action policy is defined (race-blind or race-sighted.) We solve for decentralized equilibrium (that is, equilibrium exhibiting the externality described above) under the two policy regimes and show how and why race-blind affirmative action tends to undercut the incentive to exert effort throughout the applicant population.

In particular, we show that under race-blind affirmative action equilibrium must involve "pooling," with low ability (high cost) types in both racial groups choosing a common effort level. There are many equilibria, but the only one to survive application of the ``D1" refinement (which seems natural in our context) entails zero effort from the relatively low ability (high effort cost) applicants. So, in the model under discussion, this is the sense in which CB-affirmative action is inefficient. The greater the degree of representation sought for the disadvantaged racial group, the greater the inefficiency. Indeed, we have obtained the following result: Suppose employers practice CB-affirmative action, and let the degree of representation they seek for the disadvantaged group approach population parity. Then, in the unique decentralized equilibrium that survives the D1 criterion, no workers exert any effort and all winners are chosen by lottery with probability of winning = 1/2 in every match.

We conclude that color-blind affirmative action entails a basic tradeoff between incentives and representational goals. If firms are constrained to be color-blind but continue to value diversity, they will act in such a way as to "flatten" the function that relates a worker's probability of winning (in equilibrium, when randomly matched) to that worker's ability. Some lower ability workers must have a greater chance of winning under CB affirmative action, and some higher ability workers must have a smaller chance. (Otherwise, the disadvantaged group, which has relatively more low ability types, cannot have its representation increased.) This flattening of the link between ability and success undercuts incentives for all workers to exert preparatory effort (because raising effort is, in equilibrium, akin to pretending to be a higher ability type, and the average over applicants of the marginal return to behaving in this way must fall if the representation constraint is to be met in a color-blind fashion.) The aforementioned result follows immediately, once one recognizes that the zero-effort pool will have to contain the entire worker population if a representation constraint of population parity is to be met. This result provides a stark contrast with the color-conscious case, in which population parity can be achieved without driving effort to zero and, when the target group is small, with barely any impact at all on the equilibrium distribution of applicants' effort.

IV. Framework for Policy Analysis

Our analysis provides an analytical method for viewing all of the practices mentioned above -- XX-percent plans, voluntary test score submission, increased relative weight on non-test score criteria, preference for low SES applicants -- within a unified framework. The basic idea is to conceive of an abstract "admissions policy function" for a college or university, which associates with each applicant profile a probability of admitting that applicant. An applicant's profile is merely a list of the applicant's "score" along a number of dimensions, not all of which need be directly related to academic achievement. In general, test performance, grades in high school, letters of recommendation and interview results can be combined with information about the applicant's social background, life experience, region of origin and the like. In general the likelihood of admissions can be made to depend upon all such factors. From the perspective we are taking, factors used in such an admissions policy function, and the weight given to these factors, can be chosen by the college or university in order to meet its admissions objectives. The admissions policy will be "race-blind" if an applicant's race is not explicitly utilized as a factor in the admissions policy function. However, by taking note of the ways in which some factors that might be employed in the admissions process are differentially associated with the likelihood that an applicant belongs to one or another of the racial groups, race-blind policy functions can be devised that lead to quite varied outcomes in terms of the degree of racial diversity of the admitted class. We can envision an institution choosing among alternative race-blind admissions policies (what the Bush Administration in its brief calls "race neutral alternatives") so as to rationally pursue its interests, including its desire to admit a racially diverse class. Within this framework, all of the policies just mentioned can be captured by an artful choice of the factors utilized and the weights given to those factors in some (most generally, probabilistic) admissions policy function.

When compared to the explicit use of racial preferences, all the recent innovations in admissions policy mentioned above (voluntary test score submission, XX percent plans, class-based admissions preference, etc.) achieve a given degree of racial representation at some (possibly substantial) cost to the efficiency (properly defined) of the selection process. Of course, this by itself need not constitute an argument in favor of racial affirmative action or against the use of color-blind techniques to achieve racial diversity. But it does suggest the importance of estimating the actual magnitude of this inefficiency.

To see what is involved, imagine that a college makes reporting SAT scores optional for its applicants, and further commits itself to admit a certain fraction of its incoming class from the set of students who elect not to submit scores. This is a race-blind policy that is likely to result in more blacks being admitted, though it is not explicitly preferential to blacks. But, this policy must lead to an entering class that on average performs less well academically. The logic at work here is simple and quite general. Any college with a constraint on the number of places in the entering class that seeks to increase the presence of a group of persons (say blacks) who on average perform less well on the standard measures of academic qualification, must do two things. It must reject some non-blacks who would otherwise have been admitted, but for the desire to have more racial diversity. And, it must accept some blacks who would otherwise have been rejected. Necessarily, then, the most efficient policy is one that rejects the least qualified of the (otherwise admissible) whites, while accepting the most qualified of the (otherwise inadmissible) blacks. But, this can only be done with a racially preferential set of admissions standards. Thus, a color-blind policy (which, by definition, is NOT racially preferential) cannot be the most efficient one.

Similarly, selecting students based on rank within their local high school's graduating classes will end-up admitting some less qualified blacks, and rejecting more qualified whites, than would have been admitted and rejected if racially differential standards had been applied to the entire applicant pool. (This is because highly ranked black students at weak high schools will be admitted in the place of black students ranking just below the top of their class at strong high schools. Similarly, white students just under the line at strong schools will be rejected despite their being better qualified than white students just above the line at weak schools, who will be admitted.) Therefore, if race-contingent admissions standards are ruled out a priori, then something less than a fully efficient selection must take place, as long as a college seeks greater diversity than would occur under race-blind, strictly meritorious selection. Since a great many colleges are certain to continue pursuing diversity, even if the explicit use of race in the admissions process were to be outlawed, the adverse efficiency effects being discussed here, if substantial in magnitude, would be of more than merely academic interest.

In the exercise undertaken here, we estimate the loss of efficiency in selection resulting from an effort to obtain a given degree of racial representation. (Results reported in Table 5.) We also ask what kind of color-blind policies among the various proposals being discussed seem best suited to achieve the "second best" outcome. (Results reported in Table 7) Our simulation models are calibrated on real data to quantify this trade-off. I now want to give some indication of how we proceed

We compare the performance of three different policy regimes:

(i) Laissez Faire (LF);

(ii) Color-Sighted Affirmative Action (CS); and,
(iii) Color-Blind Affirmative Action(CB).

The admissions policy maker is assumed to take no account of a student's race, nor to make any use of non-academic factors in the admissions policy function under regime (i). The policy maker is assumed to seek a certain percentage of black students in the class to be admitted, and to do so through the use of old-fashioned racial preferences (that is, conventional affirmative action) under regime (ii). Finally, under regime (iii) the policy maker seeks the same percentage of black students as under (ii) (in expectation) but is constrained to achieve this objective without the explicit use of race in the admissions policy function. Rather the policy must rely on proxies, employ some randomization techniques, or use an artful weighting of non-academic criteria that are distributed quite differently within different racial groups in order to achieve the desired objective. This constrained policy choice is modeled as a linear programming problem. We imagine that the policy maker chooses the probability of admission to be assigned to applicants by the admission policy function so as to maximize the anticipated average academic quality of the admitted class, subject to capacity and racial representation constraints. We then compare the performance of the "best" admissions policy under each of the three regimes, and take note of how the constrained optimal color-blind policy attains its goal through the artful use of racial proxies.

We employed three academic variables: SAT math score, SAT verbal score and High School Rank; and three socioeconomic background variables: mother's education, father's education and family income. We use a simple regression analysis to associate these variables with the expected College Rank achieved by the students in the sample (whose grade histories were available from the administrative records of the participating institutions.) To calculate the laissez faire policy we simply sort the students by their academic index (i.e., their predicted college performance derived from the aforementioned regression analysis), taking the top half of these students as those to be "admitted" in the thought experiment. To calculate the color-sighted policy that preserves the original percentage of black students, we merely sort the students separately by race, and "admit" the top half of each racial group. (This is equivalent to giving the black students a "bonus" of a certain number of points in the evaluative process – as is done in the so-called "racial plus factor" admissions policy under dispute at the University of Michigan.) And, finally, to calculate the optimal color-blind policy, we estimated an auxiliary regression in which the likelihood that a given student is black is expressed as a function of that students academic and socioeconomic background variables. In effect, we imagine that the colleges are forecasting the applicant's race from the non-racial information in that applicant's profile. This forecast is used in the linear program to calculate the expected number of black students in the admitted class, under alternative admissions formulae. We solve this program to find the optimal color-blind affirmative action admissions formula -- namely, that one which maximizes the anticipated quality of the admitted class subject to the constraint of expecting to admit, on average, the desired number of black students.

V. The Data

The College and Beyond data base contains admissions and transcript records of 93, 660 full-time students who entered thirty four colleges and universities in the fall of 1951, 1976, and 1989. For the purposes of this paper, we restrict our attention to students from seven institutions in 1989. Our selection criterion is based solely on the availability of relevant data. All of our regressions include dummies for missing data. We describe below how we combined and recoded some of the College and Beyond variables we use in our analysis.

(1) SAT Math: Results of each student's performance on the mathematics portion of the Scholastic Aptitude Tests (SAT). The institutions reported each student's SAT scored. Only one SAT math score and one SAT verbal score was recorded for each student, even if the student took the test multiple times. Information is not available pertaining to which SAT score the institution reported.
(2) SAT Verbal: Results of each student's performance on the verbal portion of the Scholastic Aptitude Tests.

(3) High School Percentile: This captures the percentile rank of each student in their high school.
(4) Parental Education: Parental education information was drawn from the student's college application. Questions involving parental education varied greatly from university to university. To account for this, we aggregated the data into two categories: college degree holder or not. This was done, independently, for mother's and father's education.
(5) Family Income: This variable was taken directly from the college and beyond database. At some institutions, the financial aid office provided family income information. Some colleges' financial aid office had income information for all students who applied for aid; others had information for all students who received aid. Family income data are never available for the entire class.

VI. The Results

Our results are presented in the tables that follow. Tables 1 and 2 present summary statistics for our sample for all students and for black students, respectively, broken down by institution. Table 3 reports results from the college-specific regression equations used to predict a student's class rank after four years of matriculation, as a function of academic and socioeconomic background variables. Table 4 gives results from the auxiliary regressions that we imagine the colleges to have run in order to forecast the likelihood that a student is black, based on background variables.

Tables 5 through 7 report the results of greatest interest, regarding the relative efficiency of "race neutral alternatives" (T.5), the implication of such policies for the representation of Hispanics and Asians as well as Blacks (T.6), and the way that "optimal color-blind affirmative action" alters the weight given to various factors in the optimal admissions formula -- i.e., test scores, grades and socioeconomic background measures (T.7). (Note that the LF and CS policies both use the same weights (those derived solely from the regression predicting college class rank), while the CB policy employs weights that have been "biased" in order to exploit the fact that some variables are more closely correlated (positively or negatively) than are others with a student's being black.

The results reported in Tables 5 and 7 dramatically illustrate the main finding of this research: if an admissions office attempts to devise a system for achieving a desired degree of racial diversity while avoiding the explicit consideration of race, it would be significantly less effective at selecting students of all races who are anticipated to be high academic performers. The optimal color-blind admission policy gives less weight to test scores, more weight to high school grades, and more weight to social background factors than the optimal policy under Laissez Faire. The data from these selective colleges and universities demonstrate that the efficiency loss from using race-neutral factors to achieve racial diversity can be three to four times greater than the loss incurred under the optimal color-sighted policy. It is worth noting that avoiding the use of race while continuing to pursue the goal of racial diversity can even be less efficient (at selecting well performing students) than following an admissions system that, while ignoring racial diversity, also completely ignores the high school grade performance of applicants.

These findings are quite relevant to the current policy debate. Proponents of race-neutral alternatives to conventional affirmative action (such as the percentage plans advocated, for example, by the Bush Administration in its brief for the case *Grutter v. Bollinger* currently pending before the U.S. Supreme Court) have failed to fully reckon with the potentially significant efficiency costs of their proposals.) There are two issues here: First, as the regression results from Table 3 (with their low R-squared's show, academic performance is very difficult to predict from the test scores and high school grade profiles of an 18-year-old. (In no instance is more than one-third of the variation among students in college performance explained by variation in their academic and social background characteristics prior to entering college.) The fact is that admissions committees undertake activities -- read essays, examine a student's extra-curricular activities, acquire knowledge of the quality of instruction at particular high schools, etc. -- that add real value to the undertaking of forecasting the post-admission outcome. Race-neutral alternatives introduce formulaic evaluation practices that short-circuit this "whole file review" process and thereby impair the effectiveness of admissions screening.

Secondly, in a very general sense, the color-sighted (racial plus factor) policy must provide the most efficient method of obtaining a given degree of racial diversity. All race-neutral alternatives (like percentage plans) undertaken with the aim of generating the same degree of racial diversity must throw away information relevant to the admissions decision. As noted above, if a school can admit only a limited number of students, and desires to see more black/Hispanic students admitted (more, that is, than would be admitted if the school did nothing to promote diversity) then, compared to a state of affairs in which the school had no concern for diversity, the school must exclude some students who are not black/Hispanic and who would otherwise have been admitted, while at the same time the school must include some black/Hispanic students who would otherwise not have been admitted. The most efficient way of doing this is to exclude the least promising of the otherwise admissible non-black/Hispanic students while including the most promising of the otherwise inadmissible black/Hispanic students. A moment’s reflection allows one to see that this most efficient practice is nothing other than a "racial plus factor" policy. The results in Table 5 reveal that the efficiency gap between this policy and the next best race-neutral alternative can be substantial.

Table 1: Summary Statistics For all Students

All Students	SATmath	SATvrbl	HSpct	MOMed	DADed	FAMinc	# of students
College A	699	644	96	0.76	0.88	66620	1139
	(66)	(73)	(6)	(0.43)	(0.33)	(43825)	
College B	649	578	93	0.64	0.77	51012	1858
	(80)	(76)	(10)	(0.48)	(0.42)	(31203)	
College C	599	552	82	0.69	0.83	47714	1486
	(86)	(84)	(16)	(0.46)	(0.38)	(36471)	
College D	626	600	88	0.75	0.82	48782	829
	(91)	(94)	(11)	(0.43)	(0.38)	(29891)	
College E	595	580	90	0.73	0.84	50041	606
	(74)	(82)	(10)	(0.44)	(0.37)	(26422)	
College F	621	588	92	0.67	0.76	42840	582
	(81)	(82)	(9)	(0.47)	(0.43)	(23302)	
College G	682	655	94	0.71	0.79	20721	519
	(73)	(78)	(8)	(0.46)	(0.41)	(8042)	

Table 2: Summary Statistics for Black Students

Black Students	SATmath	SATvrbl	HSpct	MOMed	DADed	FAMinc	# of black students
College A	612	595	95	0.63	0.66	51318	82
	(65)	(66)	(5)	(0.49)	(0.48)	(37465)	
College B	541	523	84	0.48	0.45	39893	157
	(82)	(83)	(15)	(0.50)	(0.50)	(23965)	
College C	515	502	84	0.68	0.75	33799	98
	(87)	(100)	(16)	(0.48)	(0.44)	(21974)	
College D	486	486	76	0.46	0.41	38062	59
	(94)	(105)	(18)	(0.50)	(0.50)	(27209)	
College E	515	523	84	0.69	0.65	46281	24
	(73)	(95)	(17)	(0.48)	(0.49)	(27140)	
College F	501	491	82	0.45	0.42	31682	49
	(74)	(72)	(16)	(0.50)	(0.50)	(20231)	
College G	563	552	84	0.48	0.55	19438	33
	(78)	(74)	(45)	(0.51)	(0.51)	(7982)	

Table 3: Predicted College Rank

College Rank	SATmath	SATvrbl	HSpct	MOMed	DADed	FAMinc	Constant	R^2	N
College A	**7.23**	**10.67**	**7.68**	3.95	2.48	0.35	**-151.36**	0.24	1139
	(1.27)	(1.14)	(1.69)	(2.08)	(2.79)	(0.25)	(16.89)		
College B	**1.89**	**5.92**	**7.11**	**3.41**	**6.40**	-0.46	**-67.29**	0.13	1858
	(0.87)	(0.91)	(0.75)	(1.46)	(1.73)	(0.28)	(8.48)		
College C	**6.18**	**6.35**	**6.46**	**6.77**	2.71	0.09	**-85.72**	0.24	1486
	(0.85)	(0.87)	(0.53)	(3.01)	(3.65)	(0.25)	(7.39)		
College D	**4.36**	**4.55**	**4.12**	2.62	**6.84**	0.04	**-48.53**	0.13	829
	(1.24)	(1.21)	(1.05)	(2.56)	(2.93)	(0.44)	(10.13)		
College E	0.32	**8.27**	**8.38**	5.12	-0.47	0.81	**-78.56**	0.19	606
	(1.52)	(1.37)	(1.25)	(3.00)	(3.70)	(0.59)	(15.03)		
College F	**5.51**	**6.87**	**7.66**	2.85	0.18	1.05	**-101.67**	0.16	582
	(1.55)	(1.52)	(1.71)	(2.97)	(3.38)	(0.76)	(17.36)		
College G	**9.14**	**10.30**	**8.90**	4.24	4.33	-0.53	**-172.03**	0.33	519
	(1.71)	(1.58)	(1.69)	(2.63)	(3.02)	(4.18)	(18.83)		

Notes: College Rank is percentiles in distribution of cumulative GPA among class of 1989 marticulants of that College. HSpct is students' percentile in his high school. Momed and Daded are dummies for students mother and father being College Educated. Bold coefficients are five percent significant. Increments: SAT variables 100 points, HSpct 10 percentiles, FAMinc 10000 dollars. We used dummies for the missing data. (Coefficients for these variables are not reported in this table).

Table 4: Probability of Being Black Regression

Black	SATmath	SATvrbl	HSpct	MOMed	DADed	FAMinc	Constant	R^2	N
College A	**-11.97**	-1.33	1.34	**3.74**	**-5.51**	-0.36	**93.78**	0.24	1139
	(1.14)	(1.03)	(1.52)	(1.87)	(2.51)	(0.23)	(15.17)		
College B	**-9.99**	**-2.26**	**-6.14**	1.89	**-8.51**	**-0.90**	**156.53**	0.23	1858
	(0.79)	(0.82)	(0.68)	(1.32)	(1.56)	(0.25)	(7.66)		
College C	**-7.05**	**-3.62**	**1.16**	2.16	0.19	**-0.88**	**68.06**	0.13	1486
	(0.78)	(0.80)	(0.48)	(2.76)	(3.35)	(0.23)	(6.78)		
College D	**-6.94**	**-2.63**	**-4.49**	2.00	**-13.08**	-0.23	**117.11**	0.25	829
	(1.03)	(1.00)	(0.87)	(2.13)	(2.43)	(0.36)	(8.40)		
College E	**-4.83**	**-2.53**	**-1.83**	1.01	-2.14	-0.10	**67.12**	0.08	606
	(1.10)	(0.99)	(0.90)	(2.16)	(2.67)	(0.43)	(10.84)		
College F	**-10.07**	**-6.87**	**-7.32**	2.04	-4.92	-1.50	**189.40**	0.31	582
	(1.35)	(1.34)	(1.50)	(2.60)	(2.96)	(0.67)	(15.21)		
College G	**-10.10**	**-3.80**	**-6.90**	0.00	-0.66	-2.29	**180.86**	0.25	519
	(1.54)	(1.42)	(1.52)	(2.36)	(2.71)	(3.75)	(16.88)		

Notes: Dependent variable is student's probability of being black times 100. HSpct is students' percentile in his high school. Momed and Daded are dummies for students mother and father being College Educated. Bold coefficients are five percent significant. Increments: SAT variables 100 points, HSpct 10 percentiles, FAMinc 10000 dollars. We used dummies for the missing points. (Coefficients for these variables are not reported in this table.)

Table 5: Relative Performance of Color-Blind and Color-Sighted Policies

	Relative Performances:		
	CS	CB	LFw/oHSpct
College A	98.80	94.18	99.45
College B	98.98	94.95	97.96
College C	99.88	98.85	96.03
College D	98.62	91.73	99.10
College E	99.49	97.81	97.10
College F	98.28	91.90	97.52
College G	97.80	86.67	99.47

Notes: Predicted College Rank of a student is estimated by the OLS regression. (Regression Results are given in Table 3). 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 LF's Performance as 100. For example CS's Relative Performance=(CS's Performance *100)/(LF's Performance)

(ii) In all the policies, College admits half of the hypothetical admission pool. (Admission Pool is all the marticulated students of the College). The maximization problem for each policy is as follows.

a-) LF: The College maximizes its performance without any constraints. That is the College admits the students with the higher predicted College Rank.

b-) CS: The College maximizes its performance such that it admits half of the non-black and half of the black students from the admission pool. That is, College admits the half of the non-black students with the higher predicted College Rank and it admits half of the black students with higher predicted College Rank.

c-) CB: The College cannot use the race information directly. So it uses the results of the regression where it computes for each student, the probability of being black. (Results of the regression is given in Table 4). Then the College maximizes its performance such that it admits half of the non-black students (in expected terms) and half of the black students (in expected terms). In other words, the sum of the probabilities of being black of all students admitted is equal to the half of the black students in the admission pool.

d-) LFw/oHSpct: This is the same as LF with a minor change. The College cannot use the HSpct information of each student. But they know the average HSpct of the admission pool and the regression coefficient of the HSpct from Table 1. So the College assumes that each student has the mean HSpct and recalculate the expected College Rank of the student. Then, College admits the better half of the students with respect to this new expected College Rank. The Performance of the Policy is calculated by using the original expected College Rank of the students. That is the performance of the policy is the average expected college rank (original) of the admitted class.

Table 6: Diversity

	Blacks			Hispanics			Asians			Whites		
	CS	CB	LF	CS	CB	LF	CS	CB	LF	CS	CB	LF
College A	41	43.79	3	4	17	6	70	69.21	75	454	439	485
College B	78	66.37	12	7	14	8	173	132	181	670	715.63	726
College C	49	52	29	18	23	18	37	42.37	39	634	618.63	651
College D	29	29	3	2	9	2	35	36	40	340	328	364
College E	12	13	7	3	5	3	28	28	29	254	253	258
College F	24	24.2	1	4	14	4	68	53.8	74	187	187	204
College G	16	19.6	0	1	9	1	28	26	31	214	204.4	227

Note: This table shows the effects of LF, CS and CB policies on the composition of the admitted class. Note that CB policy is targeted for black students only. The number of students are not integers under CB policy. This is because, College assigns an admission probability for two students strictly between zero and one. The College has a linear programming problem: to maximize a linear function with respect to some linear constraints. The College assigns a value to each student (with respect to his expected College rank and Probability of being black) and admits the students with higher values. However, on the margin College is indifferent between two students. (two students has equal values). That is why admitting a fraction of these students is consistent with the result being optimal.

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

	SATmath		SATvrbl		HSpct		MOMed		DADed		FAMinc	
	LF	CB	LF	CB	LF	CB	LF	CB	LF	CB	LF	CB
College A	7.23	-4.77	10.67	9.34	7.68	9.03	3.95	7.70	2.48	-3.05	0.35	-0.01
College B	1.89	-3.92	5.92	4.61	7.11	3.54	3.41	4.51	6.40	1.45	-0.46	-0.99
College C	6.18	2.43	6.35	4.43	6.46	7.08	6.77	7.92	2.71	2.81	0.09	-0.38
College D	4.36	-1.07	4.55	2.49	4.12	0.60	2.62	4.19	6.84	-3.40	0.04	-0.14
College E	0.32	-5.15	8.27	5.40	8.38	6.31	5.12	6.26	-0.47	-2.89	0.81	0.7
College F	5.51	-2.00	6.87	1.75	7.66	2.19	2.85	4.36	0.18	-3.48	1.05	-0.07
College G	9.14	-3.97	10.30	5.37	8.90	-0.05	4.24	4.24	4.33	3.46	-0.53	-3.5

Notes: Increments: SAT variables 100 points, HSpct 10 percentiles, FAMinc 10000 dollars.

Both LF and CB are linear maximization problems. The College assigns a Value to each student and admits half of the students with higher Values. This table lays down the formula to calculate this Value. The numbers that are given are simply the coefficients to calculate the Value of a student. For instance, College A is considering two students with all characteristics the same but the SAT scores and Parental Education under Laissez Faire Policy. Student 1 has an SATmath score 100 points higher than Student 2, but he has both parents not college educated. Student 2 has both parents educated. College A gives more Value to Student 1 than to Student 2, because Student 1 gets "7.23" more for his high SAT score and less only "3.95+2.48" for both his parents not being College educated.

For LF: Value is equal to the expected College Rank of the student. The numbers of the table for LF columns is directly copied from Table 1. (Regressors of College Rank regression).

For CB:Value=expected College Rank of the student+λ* (student's probability of being black). We calculate λ by exploiting the fact that there are students who has an admission probability which is strictly between zero and one (The probabilities are computed by Mathematica). For those students the College assigns the same value.