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Can Socioeconomic Status Substitute for Race in Affirmative Action College Admissions Policies? Evidence From a Simulation Model

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Abstract

This paper simulates a system of socioeconomic status (SES)–based affirmative action in college admissions and examines the extent to which it can produce racial diversity in selective colleges. Using simulation models, we investigate the potential relative effects of race- and/or SES-based affirmative action policies on the racial and socioeconomic distribution of students in colleges. These simulations suggest 3 important patterns: (a) practical SES-based affirmative action policies do not yield nearly as much racial diversity as do race-based policies; (b) there is little evidence that affirmative action policies produce systemic academic mismatch; on average, affirmative action policies do not sort minority students into colleges for which they are academically unqualified; and (c) the use of affirmative action policies by some colleges affects enrollment patterns in other colleges.

Keywords: SES-based affirmative action, race-based affirmative action, policy simulations

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In its 2013 decision in *Fisher v. University of Texas at Austin*, the Supreme Court upheld the concept of affirmative action but issued a challenge to university administrators and scholars: In order to use race-based affirmative action, they must show "that no workable race-neutral alternatives would produce the educational benefits of diversity" (*Fisher v. University of Texas at Austin*, 2013, p. 11). The decision acknowledged that racial diversity is a legitimate goal of public university admissions policies, but the court expressed skepticism about whether race-based affirmative action policies were necessary to achieve that goal. In June 2015, the court agreed to rehear the *Fisher* case during its 2015–2016 term. Both the 2013 *Fisher* decision and its pending review by the court suggest that it is crucial that we understand the relative effectiveness of different types of admissions policies to increase racial diversity in selective colleges.

One potential workable race-neutral alternative admissions policy that might yield racial diversity at selective universities is affirmative action based on socioeconomic status (SES) rather than race. Such policies would presumably avoid the constitutional challenge of racial discrimination. But can SES-based policies produce sufficient racial diversity to satisfy the state's legitimate educational interests? This paper addresses that question.

This is, of course, a hypothetical question; few colleges currently use affirmative action based on SES in any substantial way. As a result, standard methods for evaluating existing policies cannot tell us how well they work. Moreover, college admissions and enrollment decisions at different universities are interdependent: Because students can apply to many colleges but enroll in only one, changes in admissions policies at one school may affect enrollment patterns at other schools. As a result, even if we knew the impacts of SES-based affirmative action in one university, those findings might not indicate what would happen if such policies were implemented in many universities. Given the hypothetical nature of SES-based affirmative action and the interdependent nature of the university admissions and enrollment processes, one very useful approach to understanding the potential impacts of different admissions policies is to use simulation models informed by the best available data. Well-designed simulations can allow rapid experimentation with a variety of policies and provide insight into the probable effects of these policies on both individual universities and on the higher education system as a whole. Although simulations are certainly not definitive about what would actually happen under a given policy, they can describe patterns of probable outcomes under assumptions that are derived from other research and provide guidance regarding the effectiveness of different types of policies. With these aims in mind, this paper uses a simulation model to investigate the dynamic effects of various types of affirmative action college admission policies.

Current Patterns of Racial Diversity at Selective Colleges and Universities

Any race-neutral affirmative action approach faces a difficult challenge. Even with the legality of race-conscious affirmative action policies, racial minority students remain underrepresented in higher education, particularly at selective institutions. Very selective colleges (those colleges with Barron's selectivity rankings of 1, 2, or 3[1]) have many more White, and many fewer Black and Hispanic, students than the U.S. population of 18-year-olds overall. This distribution is evident in Figure 1, which shows the postsecondary enrollment status of members of the high school class of 2004 by race and type of college or university. In this figure, the width of each bar represents the percentage of the college-age population enrolled in different types of colleges and universities (or not enrolled in any college, in the case of the leftmost bars); the vertical dimension describes the racial composition of students enrolled in each type of postsecondary institution. Appendix A includes a comparable figure describing the socioeconomic composition of postsecondary institutions.

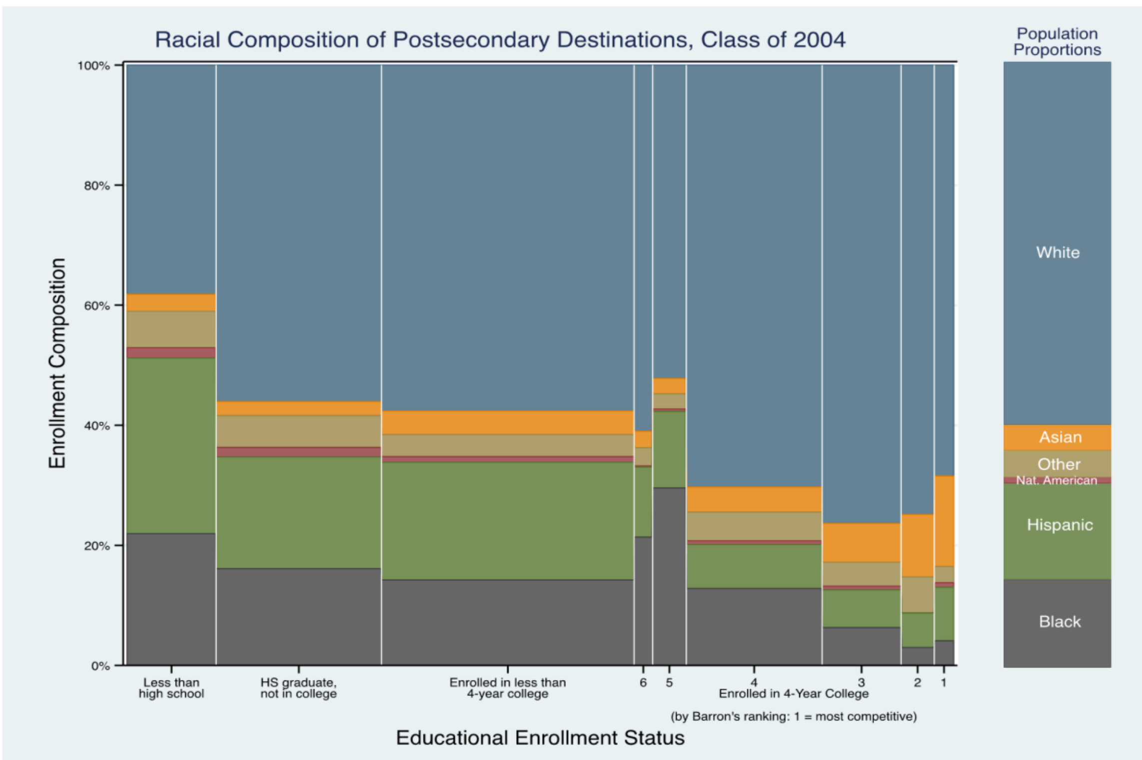


Figure 1. The racial composition of postsecondary destinations for the Class of 2004. Reprinted from* Agent-Based Simulation Models of the College Sorting Process *(CEPA Working Paper), by S. F. Reardon, M. Kasman, D. Klasik, D., & R. B. Baker, 2014, Stanford, CA: Stanford University, Center for Education Policy Analysis. Copyright 2014 by S. F. Reardon, M. Kasman, D. Klasik, D., & R. B. Baker. Used with permission.

In general, Black and Hispanic enrollment is lower in more selective colleges and universities. The most highly selective colleges, however, are slightly more racially diverse than those just below them in the selectivity rankings. This difference may be the result of race-based affirmative action policies used in some of these most selective colleges. Although one does not know what the racial composition of these most selective colleges would be in the absence of any race-based affirmative action, their enrollments would likely consist of fewer than 10% Black and Hispanic students (note that Black and Hispanic students make up about 30% of the population of 18-year-olds).

Race-Neutral Affirmative Action Policies

Proposed alternatives to race-based affirmative action policies generally take one of two forms: percent plans and SES-based affirmative action policies. Percent plans have been implemented in the three largest states—California, Texas, and Florida. Evaluations of these policies indicate they have not been effective at maintaining preban racial diversity levels in the event of a ban on affirmative action (e.g., Arcidiacono & Lovenheim, 2014; Bastedo & Jaquette, 2011; Howell, 2010; Long, 2004, 2007).[2]

The failure of percent plans to deliver on their promise has, in part, prompted some scholars and colleges to propose an alternative race-neutral form of affirmative action, one that relies on SES instead of race to determine admissions preferences (Gaertner & Hart, 2013; Kahlenberg, 1996). Under SES-based affirmative action, students are given an admissions advantage because of their socioeconomic background rather than their race or ethnicity. The presumption is that such plans can effectively capitalize on the correlation between race and income in order to construct a racially diverse class of students. The potential effects of such policies are not clear. Some existing research suggests that substituting SES for race in college admissions decisions can at least partly maintain rates of minority enrollment while increasing college access for economically disadvantaged students (Carnevale & Rose, 2004; Carnevale, Rose, & Strohl, 2014; Gaertner & Hart, 2013; Kahlenberg, 2012). Other research suggests that SES is not a sufficiently good proxy for race for SES-based policies to be effective at producing substantial racial diversity (Gaertner & Hart, 2013; Kane, 1998; Reardon & Rhodes, 2011; Reardon, Yun, & Kurlaender, 2006). At the very least, SES-based affirmative action may help to increase socioeconomic diversity on college campuses, which in and of itself may be a desirable outcome for colleges. It is difficult to evaluate the effects of SES-based affirmative action in practice, however, because such plans are not widely used.

Our aim in this paper is to develop general intuition about SES-based affirmative action and the extent to which it can replicate, or even improve, the modest levels of racial diversity evident in selective colleges under current admissions practices. Specifically, we investigate the potential relative effects of race- and/or SES-based affirmative action policies on the racial and socioeconomic distribution of students into colleges.

In addition to this basic question of the potential for policy efficacy, we also investigate two other issues relevant to the assessment of affirmative action policies. First, some critics of race-based affirmative action claim that it does a disservice to racial minority students because it places them in environments where their academic preparation systematically falls below that of their peers (e.g., Arcidiacono, Aucejo, Coate, & Hotz, 2012; Sander, 2004). This mismatch might lead to within-college racial segregation based on academic background and/or a lower likelihood that minority students admitted under affirmative action will complete college (Arcidiacono, Khan, & Vigdor, 2011). Other studies, however, indicate no significant negative effects of academic mismatch (Bowen & Bok, 1998; Dillon & Smith, 2015). In order to inform this line of research, we use our simulations to assess the extent to which race- and SES-based affirmative action policies might place minority students in colleges where their achievement falls substantially below that of their peers.

Second, we attend to the effects that affirmative action policies at one or more colleges have on enrollment patterns at other schools. College admission and enrollment processes take place in an interrelated, dynamic system where admissions policies at one college might affect enrollment patterns at other colleges. A college using a race-conscious affirmative action admissions policy might admit and enroll minority students who might have enrolled at other colleges of similar quality if the affirmative action policy were not in place. Such patterns might lead, therefore, to greater racial diversity at colleges using affirmative action but lower diversity at peer schools not using such a policy. The number of colleges using particular affirmative action policies may therefore affect enrollment patterns throughout the system, and diversity gains in some colleges may be offset in whole or in part by diversity losses in others. Our simulations here provide some insight into these potential system-wide, dynamic effects of affirmative action admissions policies.

The Utility of Agent-Based Simulation

We build intuition about the effects of different admissions policies using an agent-based simulation model (ABM), which incorporates a realistic and complex (though certainly highly stylized) set of features of the college application, admission, and enrollment processes. By using an ABM, we are able to compare the effects of a range of policies on enrollment patterns in a way that takes into account how a policy would affect the full system of colleges. This model allows us to investigate how affirmative action policies might affect university composition in a world in which students (a) have somewhat idiosyncratic preferences about colleges, (b) have some uncertainty about their own admissibility to each college, and c) use their resources and limited information to strategically apply to a small subset of colleges, and in which colleges (a) differ in their use of affirmative action policies, (b) have idiosyncratic perceptions and preferences regarding students, and (c) strategically admit enough students to fill their seats under the expectation that not all students admitted will enroll. Although this model falls short of being completely realistic, it captures important dynamic features of the application/admissions/enrollment processes that enable us to investigate the ways that affirmative action might affect enrollments.

This simulation approach improves upon previous assessments of SES-based affirmative action in several important ways. First, unlike prior simulations, it models a dynamic system of colleges, rather than a single, static college. Both Gaertner and Hart (2013) and Carnevale et al. (2014) simulated effects of just one cohort of students applying to college in one year and, in the case of Gaertner & Hart, at just one university. Gaertner & Hart, for example, simulated the effects of SES-based affirmative action using real university applicants to the University of Colorado. Their simulation, by its nature, does not incorporate dynamic processes: It provides no intuition on how application behavior might change as subsequent cohorts of students learn how the policy might affect their likelihood of admission nor on how enrollment patterns at the University of Colorado might differ if other colleges also changed their admissions policies. Our simulation, in contrast, allows student behavior to change in response to different admission policies and investigates the enrollment patterns across an entire system of colleges.

Second, our simulation approach is more realistic than other simulations in some important ways. Whereas the simulation in Carnevale et al. (2014) assumed that all students apply to all colleges, our model has students strategically applying to a small portfolio of colleges based on their (imperfect) assessments of college quality and their likelihood of admission. Moreover, in the Carnevale et al. simulation of SES-based affirmative action, the model measures socioeconomic disadvantage using many variables not typically available to admissions officers (for example, the percentage of individuals in an applicant's neighborhood who hold a college degree). Our model, in contrast, uses an index that is implicitly based on the types of factors (family income, parental education, parental occupation) that would be available to admissions officers.

Simulating the Mechanics of Affirmative Action Policies

Selective colleges generally try to admit classes of students that are both academically qualified and also diverse along numerous dimensions. These dimensions may include not only race or SES, but also academic interests, extracurricular talents, geography, and other factors. For example, colleges may want to boost enrollment in an undersubscribed major or program or find talented players for their sports teams. Selective colleges across the country demonstrate admissions preferences for these students who will add to the different types of diversity of their campus. These preferences—as well as racial or socioeconomic diversity preferences—are typically enacted through a holistic review process in which the overall academic preparation of an applicant is assessed across a host of dimensions.

Because it is part of a holistic process, the added weight given in the admissions process to students' nonacademic characteristics such as race is not explicit or directly measurable.

Indeed, by law it cannot be: The Supreme Court has prohibited colleges from assigning numeric values to race-based characteristics (*Gratz v. Bollinger*, 2003). That is not to say, however, that the net average admissions weight given to a characteristic like race (or athletic prowess, for that matter) cannot be quantified after the fact given the right data. One can ask, for example, how much higher, on average, are the grade point averages (GPAs) of admitted White students than those of admitted Black students. The answers to questions of this type provide a way of quantifying the weight given to race and factors associated with race in a holistic admissions process. A nonzero answer to this question does not, however, imply that admissions officers simply add a certain number of GPA points to each Black student's score and then admit all students simply on the basis of their (adjusted) GPA.[3]

To make the simulations in this paper realistic, we simulate a holistic admissions process in which race and/or SES are given more or less (or no) weight in admissions decisions. For this, we need a sense of the average weight given to these factors by actual selective colleges and universities so that the simulations produce patterns that are grounded in real-world data. Several existing papers have attempted to estimate the relative weight of race, SES, and academic record in admissions decisions at selective colleges; we review these in some detail in Appendix B, where we also conduct our own simple analysis. The results of our analyses suggest that Black and Hispanic applicants to the most selective colleges receive an implicit admissions weight that is roughly equal to that weight given to a 1.3 standard deviation increase in academic performance (in other words, the difference in the probability of admission of White and Black or Hispanic students is roughly equal to the difference in the probability of admission of two students of the same race whose academic performance differs by 1.3 standard deviations). We find very little or no evidence of racial preferences in admissions to colleges in lower selectivity tiers (for details, see Appendix B, Table B1).

We find evidence of slight SES-based affirmative action in the most selective colleges (the weight given to a standard deviation difference in family SES is roughly the same as given to a 0.15 standard deviation difference in academic record). Moreover, students applying to less selective colleges appear to be penalized for their lower SES in the admission process (in these colleges higher SES students were given implicit preference in admissions). The SES weights are, however, relatively small in all cases, reflecting perhaps the fact that existing SES-based admissions preferences work in two directions: On the one hand, most colleges rely heavily on student tuition and must take ability to pay into account in admissions; on the other hand, many colleges, particularly very selective colleges, actively recruit and admit low-SES students (for details, see Appendix B, Table B2).

This finding suggests that racial affirmative action plays (or played, in 2004) some role in admissions to highly selective colleges but SES-based affirmative action did not. We reiterate that our estimates in Appendix B are designed more to provide rough estimates of the average weight given to race in admissions processes than to precisely measure the impact of affirmative action policies. We use these estimates to determine the range of race and SES weights to use in the simulated affirmative action policies in our models.

Method

We use a modification of the agent-based model (ABM) of college applications, admissions, and enrollment developed by Reardon, Kasman, Klasik, and Baker (2014). Their model included two types of entities: students and colleges. We set up the model with 10,000 new college-age students per year, each of whom applied to a set of colleges. In the Reardon et al. (2014) model, students had only two attributes: family resources and academic records. We assigned each student a race as well. The race-specific distributions of academic achievement and resources, and race-specific correlations between resources and academic achievement were constructed to match the characteristics of the high school class of 2004.[4] The parameters used in our model are presented in Table 1.

For simplicity, as well as the availability of real-world data, we limited our model to the four largest racial groups in the United States: White, Hispanic, Black, and Asian. Five percent of the students in the simulation are Asian, 15% are Black, 20% are Hispanic, and 60% are White, roughly similar to actual proportions of the college-age population. The family resources measure is meant to represent the economic and social capital that a student can tap when engaging in the college application process (e.g., income, parental education, and knowledge of the college application process) and is based explicitly on the SES index variable from the Educational Longitudinal Study (ELS). The family resource measure is standardized to have a mean of 0 and standard deviation of 1. The academic record represents the academic qualities that make a student attractive to a college (e.g., test scores, GPA, high school transcripts). We constructed our sample of simulated students to match the joint distribution of race, SES, and composite math and reading scores in the ELS sample. We converted the scores from the original ELS test score scale to one that approximates the 1600-point *SAT*® scale (mean 1000, standard deviation 200) because of the ubiquity of this scale in general as well as in existing literature on affirmative action policies.

There are 40 colleges in our simulated model, each of which has a target enrollment for each incoming class of 150 students, meaning there are a total of 6,000 seats available for each cohort of students. The ratio of total students to total college seats was selected to be roughly the same as the proportion of 2002 tenth graders who attended any type of college by 2006.[5] The only attribute that colleges have is quality (perhaps better thought of as *reputation*, though in the real world the two are generally conflated in public perception).

Table 1 Agent-Based Simulation Model (ABM) Parameters

Parameter	Value	Source
Number of students	10,000	n/a
% White	60%	Institute of Education Sciences, 2012
% Black	15%	Institute of Education Sciences, 2012
% Hispanic	20%	Institute of Education Sciences, 2012
% Asian	5%	Institute of Education Sciences, 2012
Number of colleges	40	n/a
College capacity	150 students/college	n/a
Student achievement		ELS
White	*achievement~N(1052, 186)*	
Black	*achievement ~N(869, 169)*	
Hispanic	*achievement ~N(895, 185)*	
Asian	*achievement ~N(1038, 202)*	
Student resources		ELS
White	*resources* ~*N*(.198, .657)	
Black	*resources* ~*N*(-.224, .666)	
Hispanic	*resources* ~*N*(-.447, .691)	
Asian	*resources* ~*N*(.012, .833)	
Resources-achievement correlations		ELS
White	*r* = 0.395	
Black	*r* = 0.305	
Hispanic	*r* = 0.373	
Asian	*r* = 0.441	
Quality reliability (how well students see college quality)	0.7 + *a*(*resources*); *a* = 0.1	Reardon et al., 2014
Own achievement reliability (how well students see their own achievement)	0.7 + *a*(*resources*); *a* = 0.1	Reardon et al., 2014
Achievement reliability (how well colleges see student achievement)	0.8	Reardon et al., 2014
Apparent achievement (perceived achievement, increased or decreased through achievement enhancement)	*perceived achievement* + *b*(*resources*); *b* = 0.1	Becker, 1990; Buchmann et al., 2010; Powers & Rock, 1999; Reardon et al. 2014
Number of applications	4 + INT[*c*(*resources*)]; *c* = 0.5	ELS

Note. Quality and achievement reliability bound by minimum values of 0.5 and maximum values of 0.9. ELS = Educational Longitudinal Study.

Quality is operationalized as the average academic achievement of students enrolled in the school. In the real world, this mean academic achievement is probably correlated with, but not the same as, the quality of educational experience for students at a given college. Quality is measured in the same units as student academic achievement.

The model iterates through three stages during each simulated year: application, admission, and enrollment.[6] During the application stage, a cohort of prospective students observes (with some uncertainty) the quality of each of the 40 colleges in a given year and selects a limited number of colleges to which to apply based on their (uncertain and somewhat idiosyncratic) perceptions of the quality of each college and of their probability of admission to each. In the admission stage, colleges observe the academic records of students in their applicant pools (again, somewhat uncertainly and idiosyncratically) and admit those they perceive to be most qualified, up to a total number of students that colleges believe will be sufficient to fill their available seats based on yield information from previous years. During this stage, some colleges use affirmative action strategies that take students' race, SES, or both, into consideration when they evaluate students' academic records. In the enrollment stage, students compare the colleges to which they have been admitted and enroll in the one that they perceive to be of highest quality. At the end of each simulated year, college quality (again, think *reputation*) is updated based on the average academic records of students who enrolled in that year. These three stages are repeated in the next year with a new set of 10,000 students and the same set of colleges.

Although the model abstracts away many of the complexities of the actual application process, we introduced several elements into our model that were intended to mimic real-world college selection and enrollment processes. The first are imperfect information and idiosyncratic preferences: Students do not rank colleges identically, and colleges do not rank students identically. This represents the presence of idiosyncratic preferences (e.g., a student might be impressed by a college's dormitories or a college might place a premium on talented quarterbacks) as well as imperfect information on the part of both types of agents.

Second, students do not apply to every college but instead strategically engage in the application process. Using admissions results from prior years, students estimate their probability of admission to each college, though their estimates are imperfect because they have imperfect information about each college's selectivity and about their own academic record and attractiveness. Using these probabilities and their perception of the value of each college, students determine the expected utility of applying to each college and select a set of applications that maximizes their expected utility. Although most high school students likely do not engage in such an explicit process of utility maximization in choosing where to apply to college, the algorithm applied by the students in the ABM, in conjunction with their imperfect information and idiosyncratic preferences, produced very realistic patterns of application (students apply to colleges appropriate to their academic record; Reardon et al., 2014).

Finally, we structured the model to allow students' family resources to influence the college application and enrollment process in four ways. First, students' resources and academic record are positively correlated (using the empirical race-specific correlations estimated from the ELS data); this means that high-resource students are more likely than low-resource students to apply, be admitted, and enroll in higher quality colleges. Second, students with more resources submit more applications than their lower-resource peers, increasing their probability of being admitted to a desired college. Third, students with higher resources have higher quality information both about college quality and their own academic achievement relative to other students; this increases their likelihood of applying to colleges that are a good match for their academic records. Fourth, higher resource students are able to enhance their apparent academic records (analogous to engaging in test preparation or other private tutoring, obtaining help writing college essays, or strategically participating in extracurricular activities). These features of the model are explained and calibrated by Reardon et al. (2014), who used ELS data to determine appropriate values for the parameters governing them. Reardon et al. (2014) showed that, taken together, imperfect information, idiosyncratic preferences, strategic application behavior, and socioeconomic influences create patterns of college selection and enrollment that are similar to those in the real world; low-resource students tend to apply to a limited set of lower quality colleges, while their high-resource counterparts tend to create larger application portfolios with *safeties*, *targets*, and *reaches* that increase their chances of attending a high-quality college. We held these features of the model constant across all of our simulations, and we focused always on the changes in enrollment patterns that resulted from changes in admissions policies. As a result, our inferences about the effects of admissions policies depended relatively little on the extent to which our model captured exactly all features of application and admission processes.

In order to examine the influence of affirmative action strategies, we modified the Reardon et al. (2014) ABM to allow colleges to exercise preferences for racial or socioeconomic diversity by weighting race and/or SES in the admissions process. We conducted a set of simulations, each with a different combination of affirmative action policy conditions. We first simulated a baseline scenario in which no colleges use affirmative action. We then examined scenarios in which the top four colleges (10% of all colleges) use either race- or SES-based affirmative action policies, or both. Further, we allowed colleges to use either moderate or strong versions of these policies.

In order to determine how much weight each of these simulated policies assigns to students' race or SES, we referred to the rough estimates of the relative weights evident in admissions to highly selective colleges described previously. Recall that the average weight assigned to a student's race was estimated to be roughly 1.3 standard deviations. Given this, we set our moderate affirmative action policies to assign minority status (Black or Hispanic students) a weight equal to 0.75 standard deviations (or 150 points in the SAT-like scale we used to measure academic preparation in our models); the weight is 1.5 standard deviations (300 points) in our strong affirmative action policies. Thus, strong racial affirmative action is slightly stronger than the average used by highly selective colleges today; moderate racial affirmative action is half as strong.

Likewise, moderate and strong SES-based affirmative action give students an implicit weight of plus or minus 0.375 or 0.75 standard deviations (75 or 150 points, respectively, on our scale) for each standard deviation they are above or below the average student in resources. These values are considerably stronger (two to four times stronger) than the estimated weight of SES we observed in selective college admissions in the ELS data; we chose these values to ensure that our simulations represent a significant increase over current practice in SES-based affirmative action so that they represent a plausible test of what might occur if colleges begin weighting SES much more heavily than they do at present. Moreover, while the magnitude of these SES-based affirmative action weights is half that of the corresponding race weights, recall that the SES weight is assigned per standard deviation of family resources. Because of this approach, the difference in weights between students +/- 1 standard deviation from the average resource level is 300 achievement points in the strong policy case.

Although empirical observation of college admissions in the ELS dataset suggests that only colleges in the most elite group (roughly the most selective 10% of colleges) employ racial affirmative action policies, we experimented with different numbers of colleges using moderate race-and-SES-based affirmative action in order to explore dynamic system-wide effects that result from different numbers of colleges using these policies. For these experiments, we included scenarios where the top one, four, 10, 20, or all 40 colleges use affirmative action in admissions; we also included a scenario where four of the top 10 colleges (those ranked 1, 4, 7, and 10) use affirmative action. These simulations allowed us to examine how differences in the proportion of colleges using affirmative action policies might affect admissions and enrollment patterns.

In all, we simulated admission and enrollment patterns in 37 scenarios: a baseline scenario in which no college uses any form of affirmative action, and 36 scenarios in which the six different subsets of colleges (described previously) used one of six different versions of affirmative action policies.[7] In each scenario, we allowed the model to run for 30 simulated years. In the first 15 years, no college used any affirmative action policy; this allowed the model to burn-in—to settle in an equilibrium condition in which college quality (and student perceptions of college quality) was stable from year to year. After the 15-year burn-in, the specified top-tier colleges started to use affirmative action strategies, and the model then ran for an additional 15 years. At the end of this period, we found that college quality and enrollment patterns had stabilized. We used the patterns of enrollment in the final year to assess the effects of each affirmative action scenario. We described the racial and socioeconomic composition of each college in the final year to assess the policy effects on college racial and socioeconomic diversity (in colleges both using and not using some form of affirmative action). In addition, in order to assess whether affirmative action produced academic mismatch for minority students, we described the average academic preparation of students in the colleges of students of a given race and level of academic preparation college.

Results

We start by comparing the effects of race- and SES-based affirmative action policies on the racial and socioeconomic composition of the top colleges. Figure 2 shows the racial composition among the four colleges that use affirmative action by simulated affirmative action policy. The proportion of Black and Hispanic students is positively affected by both types of affirmative action policies but increases more rapidly when the magnitude of racial affirmative action increases than when the magnitude of socioeconomic affirmative action does. This finding is evident when one compares the rate of change in the proportion of minority students in Bars 1, 2, and 3 (increasing race-based affirmative action with no SES-based affirmative action) with the rate of change in the proportion of minority students in Bars 1, 4, and 5 (increasing SES-based affirmative action with no race-based affirmative action). Bars 6 and 7 show that colleges are most racially diverse when both race- and SES-based affirmative action policies are used.

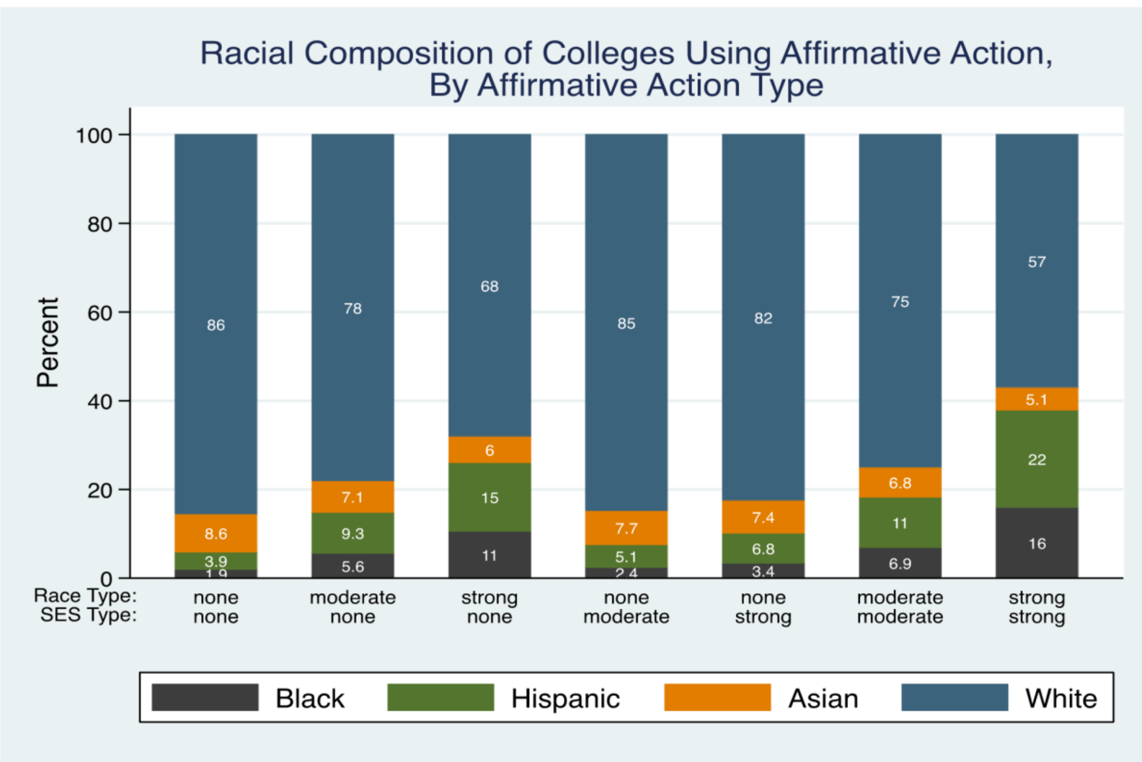
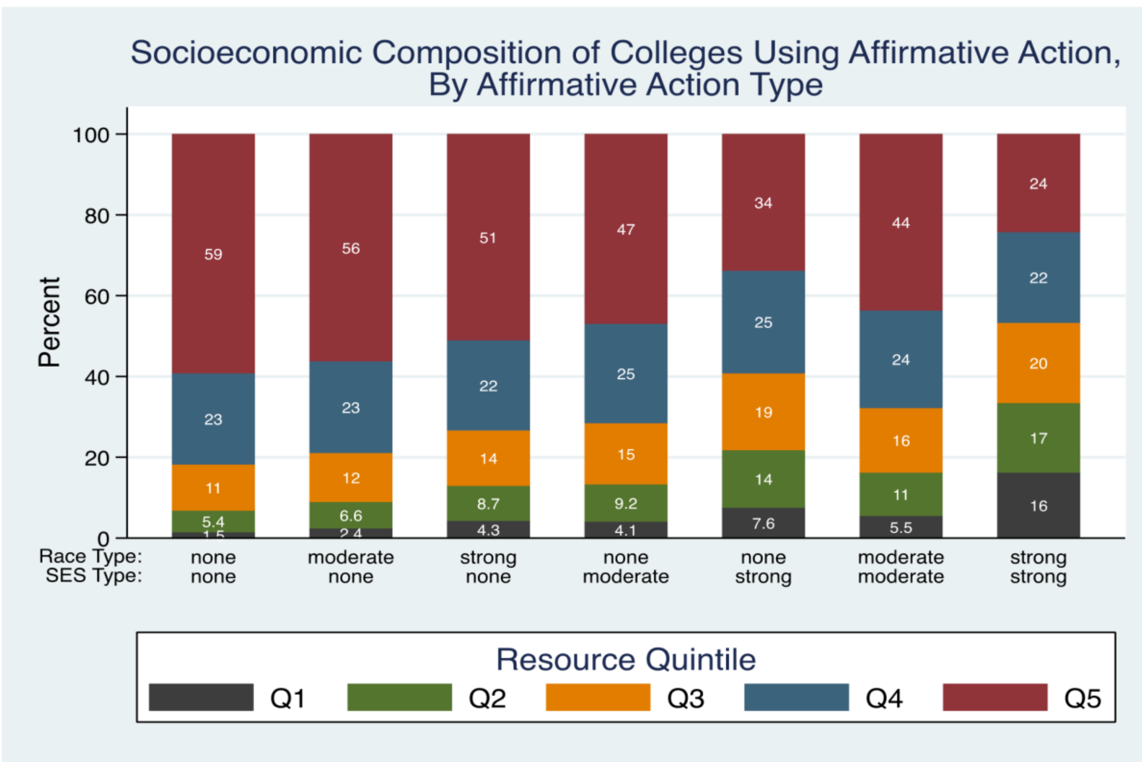


Figure 2. The racial composition of colleges using affirmative action by affirmative action type. SES = socioeconomic status.

Figure 3 shows the socioeconomic composition of colleges that use affirmative action (in terms of student resource quintiles) by simulated affirmative action policy. SES-based affirmative action policies have a large effect on the socioeconomic composition of colleges. Racial affirmative action policies, on the other hand, have a small effect, especially relative to that of socioeconomic affirmative action policies. The first quintile students—the poorest students—experience the greatest gain in overall enrollment rate under both affirmative action strategies. The highest quintile experiences the greatest reduction in enrollment. There are only small changes in enrollment for the second, third, and fourth quintiles.

Next we turn to how affirmative action policies affect the difference in academic achievement between the beneficiaries of affirmative action and the other students enrolled in their college. Figure 4 shows mean academic achievement of students' classmates in college as a function of a student's own achievement, race, and affirmative action type. Here again, only the top four colleges in the simulation use affirmative action. Race-based and the combination of race- and SES-based affirmative action policies lead Black and Hispanic students to enroll at colleges where their peers have higher average academic records relative to no race- or SES-based affirmative action policies alone (Figure 4, right panel).



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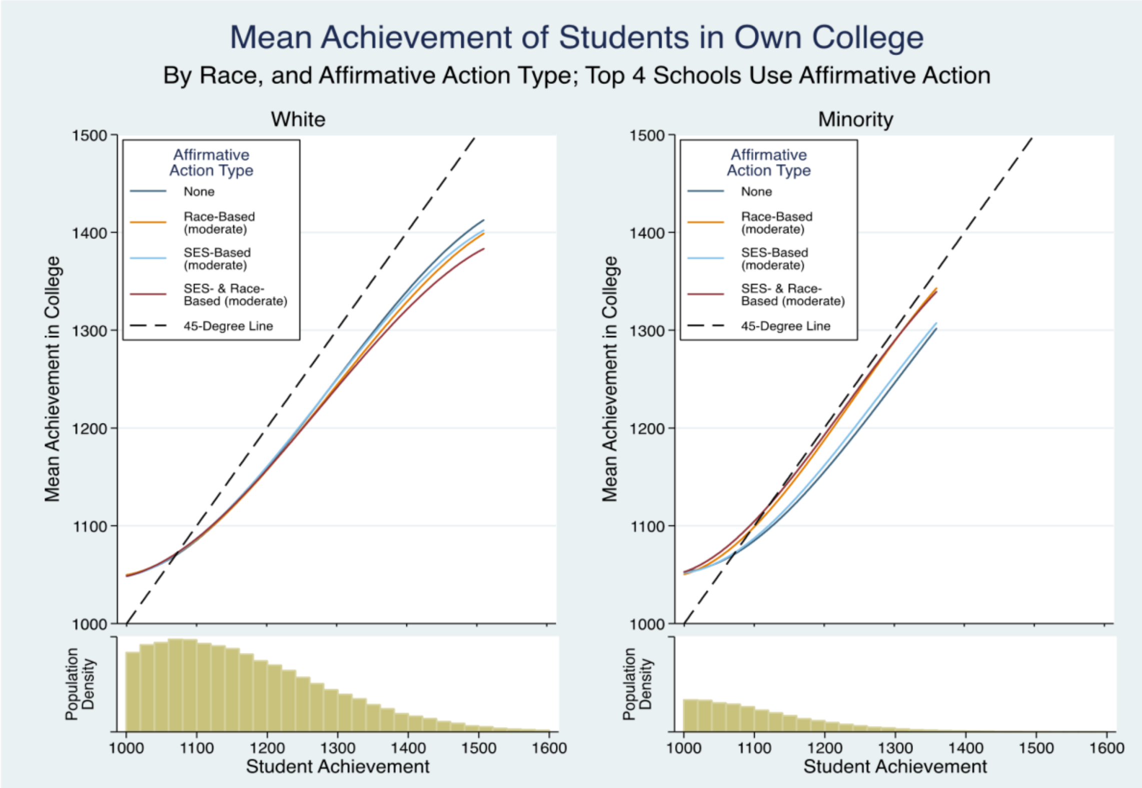

Figure 4. Mean achievement of students in own college by race and affirmative action type for the top four schools that use affirmative action. SES = socioeconomic status.

This increase in the mean academic achievement of students is experienced through most of the achievement distribution and amounts to as many as 40 SAT points (roughly 0.2 standard deviations). This consistent increase in mean achievement is evidence that on average minority students experience modestly better academic settings under affirmative action policies. Conversely, White students (left panel) experience small decreases in the mean academic achievement of their peers under all types of affirmative action, although this decrease is only appreciable under the joint SES- and race-based affirmative action policies, and only at the high end of the student academic achievement distribution. On average, most White students do not experience any meaningful changes to their academic environment as an effect of affirmative action policies.

Figure 4 also includes a 45-degree line, which corresponds to a student's own achievement. When the lines indicating the average achievement of students' peers are below the 45-degree line, this means that students, on average, have scores above the average for their school. For minority students (Figure 4, right panel) with achievement above roughly 1100 on our scale (0.5 standard deviation above the population mean achievement of 1000), the average achievement of their classmates is typically below their own achievement in each of the affirmative action scenarios shown in Figure 4. For minority students with slightly lower achievement, race-specific affirmative action does lead to them enrolling, on average, in schools where their own achievement is below the school average, but only slightly. These patterns suggest that concerns about affirmative action leading to minority students enrolling in schools for which they are not academically prepared may not be well founded.

Similar patterns are evident in Figure 5, which shows the mean academic achievement of enrolled students as a function of student academic record, low or high SES, and type of affirmative action policy. Low-SES students experience an increase in the mean academic achievement of their peers under any affirmative action policy that utilizes SES but only minor increases as a result of race-based affirmative action. This increase is relatively consistent in the upper two-thirds of the student academic achievement distribution, with the largest increases for students with achievement above 1200. High-SES students, however, see a decline in the mean academic achievement of their peers under all affirmative action policies, and particularly for the combined SES- and race-based policy.

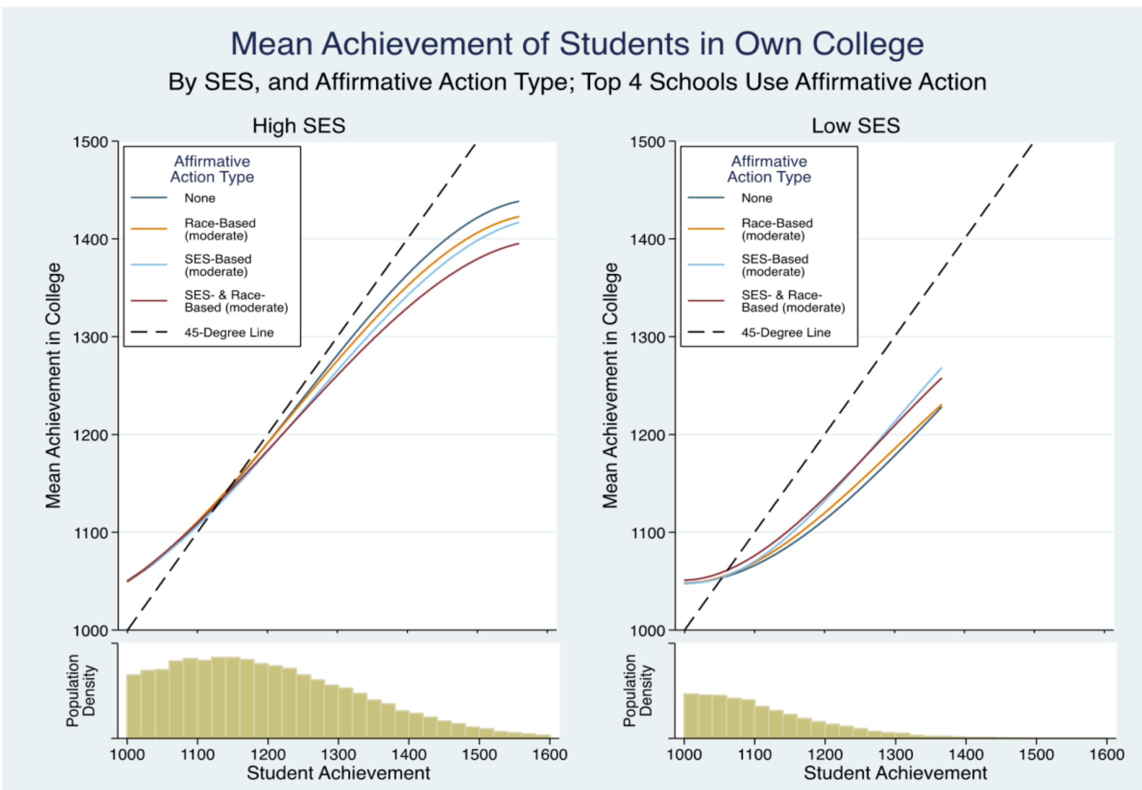

Figure 5. Mean achievement of students in own college by socioeconomic status (SES) and affirmative action type for the top four schools that use affirmative action. SES = socioeconomic status.

Although these decreases are not large through much of the student achievement distribution, they do increase as student academic achievement increases; at the high end of the student achievement distribution, the decrease is as much as 40 SAT points (0.2 standard deviations) under the joint race- and SES-affirmative action policies. Note that Figure 5 also shows no evidence that affirmative action leads to low-SES students being enrolled in schools for which they are academically unprepared.

Figure 6 describes the mean academic achievement of one's classmates by one's own achievement and race under scenarios where race-based affirmative action policies are used by different numbers of colleges. For White students (Figure 6, left panel), there is little difference in the mean achievement of peers under any affirmative action admissions policy; the lines are close throughout the distribution. For minority students, however, there are increases in the mean achievement of enrolled peers under all affirmative action policies; these gains are evident across the majority of the student achievement distribution. As one might expect, when only one college uses affirmative action, only students in the top of the achievement distribution experiences gains in peer achievement, whereas when 10 colleges use these admissions policies, students across the distribution experience gains.

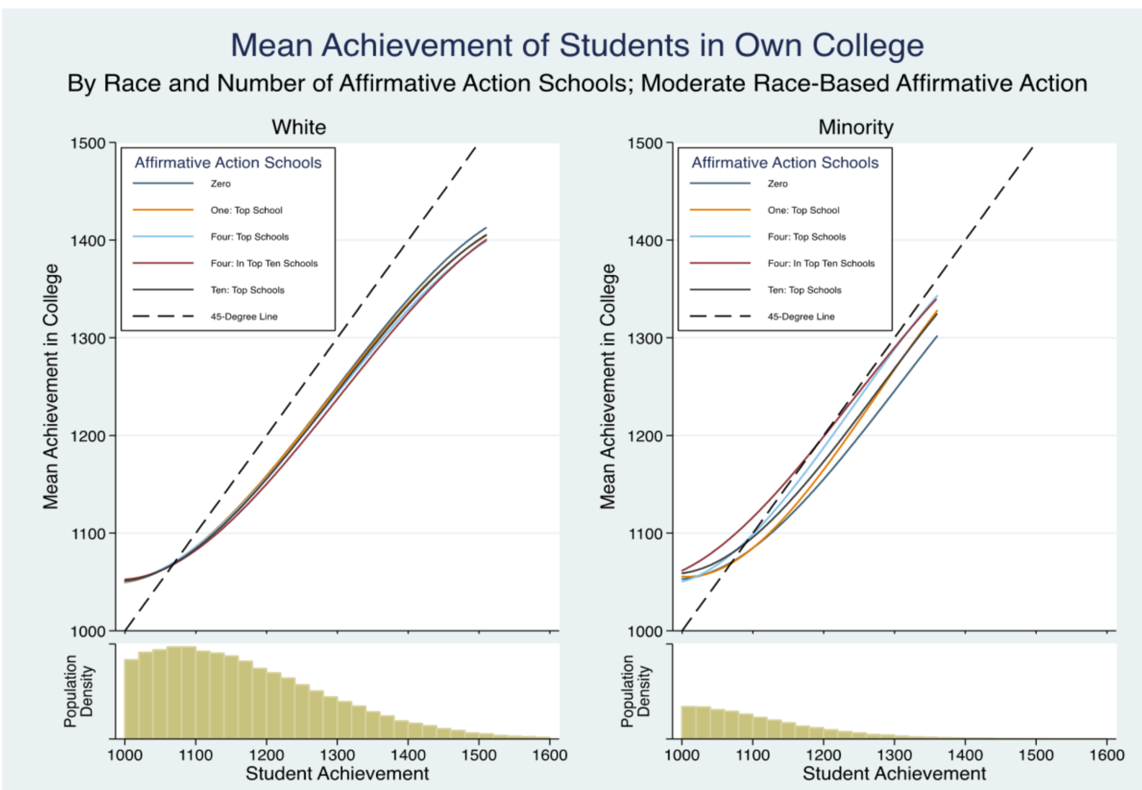

Figure 6. Mean achievement of students in own college by race and number of affirmative action schools with moderate race-based affirmative action. SES = socioeconomic status.

Because students and colleges comprise an interconnected system, the effects of affirmative action policies will not be isolated to the colleges that use them. Colleges that do not use affirmative action policies are affected by the presences of such policies in other schools. Figures 7 and 8 illustrate these system dynamics—the effect of different numbers of colleges using affirmative action policies on the kinds of students (achievement, race, and SES) enrolled in all colleges. In each of these figures, grey arrows indicate the colleges that use affirmative action and black arrows show colleges that do not. Each of the arrows starts at the location in the figure corresponding to the racial (in Figure 7) or socioeconomic (Figure 8) composition and average academic preparation of enrolled students in the college in the final year of the model's burn-in period, before any college begins using affirmative action. The arrows end at the location corresponding to each college's enrollment composition in the final year of the model, after some colleges in the model have been using affirmative action for 15 years. Note that the models are very stable at this point; letting the model run longer does not generally result in any additional systematic pattern of change. In both figures, the colleges using affirmative action policies use moderate levels of both SES- and race-based affirmative action.

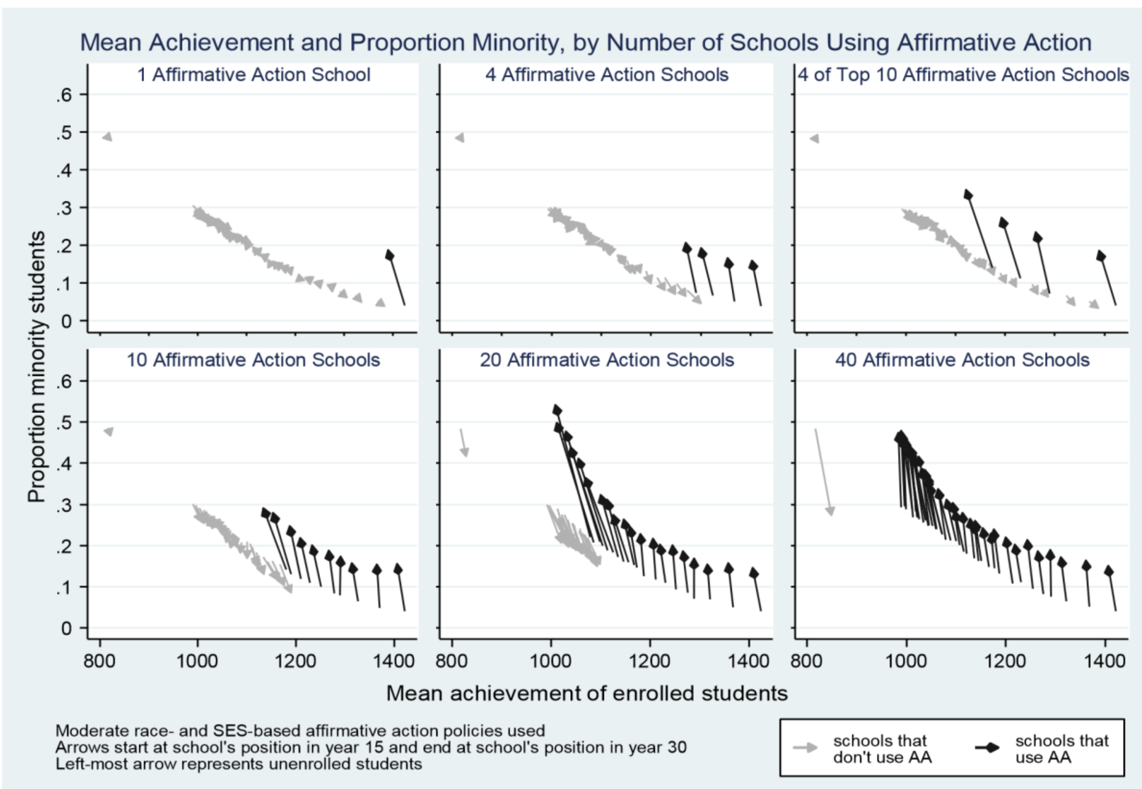

Figure 7. Mean achievement and proportion minority by the number of schools using affirmative action. SES = socioeconomic status.

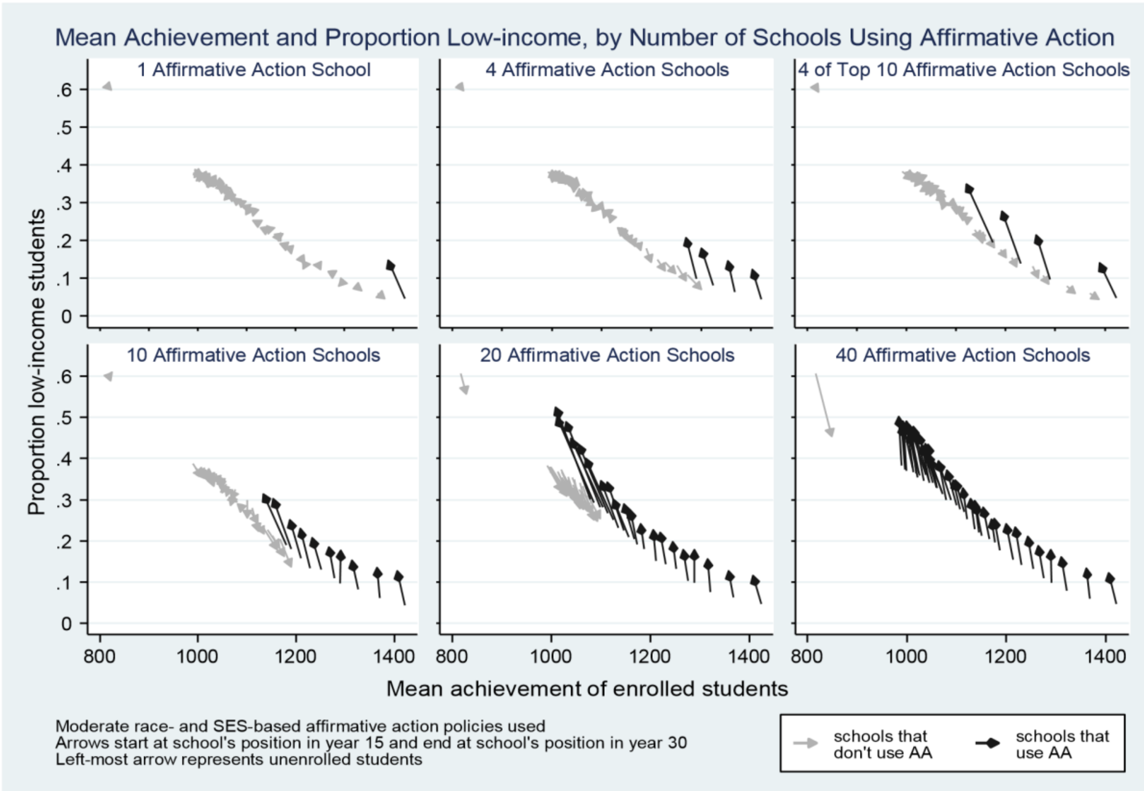

Figure 8. The mean achievement and proportion low-income by number of schools using affirmative action. SES = socioeconomic status.

A few results are immediately clear in Figures 7 and 8. First, colleges that are using affirmative action move up and to the left in the figures. That is, these colleges become more diverse (racially and socioeconomically) and their students' average achievement declines slightly. Second, the slope of these grey arrows is quite steep, which indicates that the changes in mean achievement are much less pronounced than the changes in the proportion of minority or low-income students. Third, the less selective colleges that use affirmative action experience the greatest changes in both diversity and average achievement—their lines move the farthest. Fourth, colleges that do not adopt affirmative action policies but that are close in mean achievement to those that do also experience significant changes in diversity and average achievement, though in the opposite direction as those using affirmative action. That is, they become less diverse and the mean achievement of their enrolled students increases. Fifth, the effects on colleges that use affirmative action vary relatively little by the number of colleges using affirmative action; once a school is using these admissions policies it seems to matter little whether colleges near it in quality are also using them. Finally, only in the most extreme cases (20 or 40 colleges using affirmative action policies) is the margin of college attendance affected. Under the other scenarios the arrow representing unenrolled students (the leftmost arrow) remains mostly unchanged.

Discussion

The results of our simulations suggest at least three important patterns: (a) even relatively aggressive SES-based affirmative action policies do not mimic the effects of race-based policies on racial diversity; likewise race-based affirmative action policies do not mimic the effects of SES-based policies on SES diversity; (b) there is little evidence of any systemic mismatch induced by affirmative action policies; students who benefit from affirmative action are not, on average, admitted to colleges for which they are underqualified; and (c) the use of affirmative action policies by some colleges affects enrollment patterns in other colleges as well.

Kahlenberg (1996) has argued that "class-based preferences provide a constitutional way to achieve greater racial and ethnic diversity" (p. 1064). Yet, based on our simulations, SES-based affirmative action policies do not seem likely to be effective at producing racial diversity. The SES-based affirmative action policies we simulated are fairly aggressive in terms of the weight they give to SES, and they had large effects on socioeconomic diversity, so their failure to produce substantial increases in racial diversity at elite colleges is not a result of tepid implementation. These results are consistent with Sander (1997), who found that SES-based affirmative action at the UCLA law school did not produce the levels of diversity achieved under race-based affirmative action policies.

The 2013 *Fisher* decision requires universities to prefer workable race-neutral alternatives to race-based affirmative action. Our simulations suggest that SES-based affirmative action policies would have to give a strong preference to low-income students in order to achieve substantial racial diversity. Because very few colleges now cover total student need in their aid packages, colleges would be required to provide substantial financial aid to a relatively large proportion of their students in order to implement an SES-based affirmative action policy; this would be very costly—infeasibly costly—for most public universities. However, our simulations suggest that unless SES-based affirmative action policies use just such a strong preference for lower SES students, these policies are unlikely to result in the same racial composition in colleges as under current race-based affirmative action policies.

Similarly, our models suggest that SES-based affirmative action results in considerable economic diversity in selective colleges. In contrast, race-based affirmative action alone yields relatively little socioeconomic diversity. In tandem, race and SES-based policies seem to improve both race and SES diversity beyond what is achieved using either plan in isolation. Indeed, perhaps unsurprisingly, affirmative action policies generally produce only results they are explicitly designed to produce. This is because SES-based affirmative action policies can only work to produce racial diversity (and race-based policies to produce SES diversity) if the correlation between SES and race is high. Our analysis makes clear that the correlation between SES and race is not high enough to make SES-based affirmative action a realistic alternative to race-conscious admissions policies.[8] In sum, this analysis suggests that SES-based affirmative action policies will be unable to meet the *Fisher* standard of "workable race-neutral alternatives [that] would produce the educational benefits of diversity" (*Fisher v. the University of Texa*s, 2013, p. 11).

It is also worth noting that our models suggest that affirmative action policies are unlikely to change the margin of college attendance. That is, they do not have much effect on who attends college, but only on which college they attend if they do. Unless affirmative action policies are targeted at much lower achieving students or are implemented much more widely than they currently are, these policies are unlikely to affect the overall racial and socioeconomic distribution of college attendees.

Second, while it has been argued that affirmative action can lead to academic mismatch for minority students, we find no evidence that this is a systematic result of affirmative action policies. Moderate levels of race- and/or SES-based affirmative action appear unlikely to result in high-achieving minority or low-SES students enrolling, on average, in colleges where their academic preparation was below the average level for the college they enrolled in. Similarly, we find that affirmative action has little effect on the average academic preparation of students in the colleges of the typical White and high-SES student.

These results, of course, focus on only the average level of academic preparation in a college. If affirmative action policies have effects on the spread of academic achievement within in a college, and if students' college experiences are partially segregated by academic level (by ability tracking in classes or study groups, for example), affirmative action policies may affect students' experiences in ways our models do not capture. Our results also focus on the average effects experienced by students. If affirmative action policies operate by changing the colleges that marginal students attend (that is, pushing a few students into more selective colleges), these average results could hide significant changes for some students. Although these possibilities are important to examine in greater detail, the small average changes indicate that such policies might not induce large problems with mismatch on a system-wide level. Moreover, recent analyses by Dillon and Smith (2015), for example, suggested that eliminating all academic mismatch would result in only trivial benefits.

Third, system dynamic effects are an important, and often overlooked, factor in affirmative action policies; because colleges and students are operating in an interconnected and interdependent system, the policies of one college can affect all colleges. We find that these effects are particularly strong for colleges that are not using affirmative action policies but are close in quality to schools that are. This could be a particularly important dynamic in states in which public colleges are unable to use race-based affirmative action but private colleges of similar quality can use race conscious admissions policies. This suggests that any complete assessment of affirmative action policies must attend to effects not only within colleges that use affirmative action, but also those that do not.

The models presented in this paper do not address issues of cost or financial aid. It is likely that cost and financial aid decisions will mute some of the effects of affirmative action policies unless the policies are accompanied by increased financial aid or other greatly modified tuition structures. This is a direction for future research and an area to which policy makers should pay close attention.

In *Fisher*, the Supreme Court challenged states and universities to find race-neutral strategies that can achieve educationally beneficial diversity. Racial diversity is, the court has agreed, educationally beneficial (*Grutter v. Bollinger*, 2003). The question, then, is how to best achieve such diversity in constitutionally permitted ways. Perhaps the best way would be to eliminate racial achievement and high school graduation gaps; this measure would certainly go a long way toward equalizing access to selective colleges and universities without the need for race-based affirmative action. But, although these gaps have narrowed moderately in the last two decades (Reardon, Robinson-Cimpian, & Weathers, 2015; Murnane, 2013), they are still very large, and far from eliminated.

Until racial disparities in educational preparation are eliminated, then, other strategies are needed. Our analysis here suggests that affirmative action policies based on socioeconomic status are unlikely to achieve meaningful increases in racial diversity. That is not to say that socioeconomic affirmative action would not be valuable in its own right—it would increase socioeconomic diversity on university campuses and would benefit low-income college applicants—but only that it is not an effective or efficient means to achieving racial diversity. Race-conscious affirmative action does, however, increase racial diversity effectively at the schools that use it. Although imperfect, it may be the best strategy we currently have.

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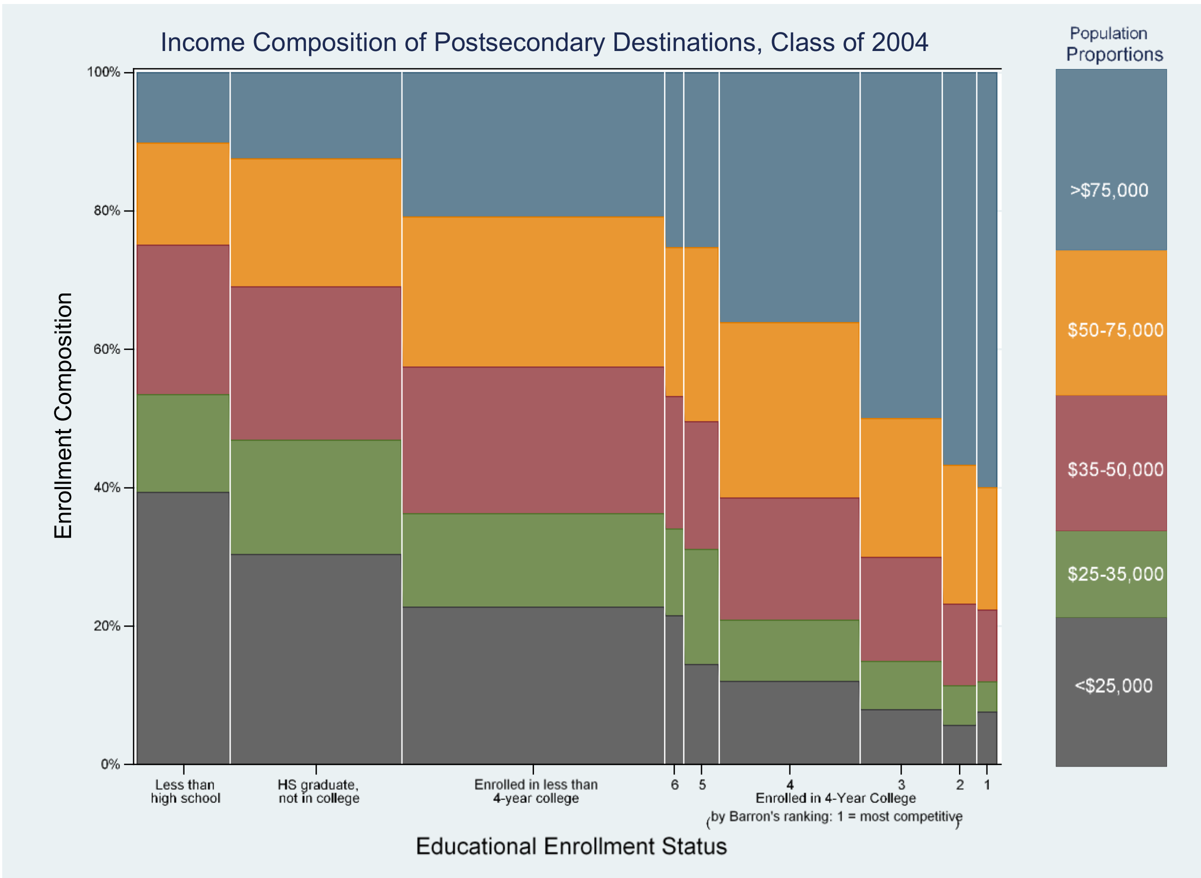
Appendix A: Income Composition of Postsecondary Destinations, Class of 2004



Appendix B: Estimates of the Relative Admissions Weight Given to Race, Socioeconomic Status (SES), and Academic Performance

We describe here our method of estimating the relative weights given to race, SES, and academic performance in selective college admissions processes. The existing methods for calculating relative admissions weights given to applicants' race, and the weights these results yield, are variable and sometimes misleading. For example, simply comparing the average academic records (such as GPAs or SAT scores) of students of different races enrolled at selective colleges can be misleading for a number of reasons. First, because of racial disparities in grades and test score distributions, we would expect the mean scores of admitted Black and White students to be different even if a college admitted solely on the basis of test scores.[9] Second, this approach cannot disentangle differences in average scores that are due to differential admission criteria from differences in scores that are due to racial differences in application or enrollment patterns.

A better approach to estimating average affirmative action weights is to use data on a pool of applicants to one or more selective colleges and to estimate the relationship between race/SES and the probability of admissions. This approach was taken by Kane (1998) and Espenshade and Radford (2009). The idea of this approach is to predict admission on the basis of race, academic, and other observable factors and then compare the coefficients on the race variables with the coefficient on SAT scores. For example, if a Black student's probability of admission was 7% greater than an otherwise observationally identical White student, one can calculate what change in SAT score would be needed to yield the same 7% boost in the probability of admission. Both Kane and Espenshade and Radford estimated the implicit weight given to race (being Black, specifically, in their models) in the admission process at selective colleges as roughly equivalent to the weight given to an additional 300–400 SAT points (as measured on the 1600 point SAT scale that was in use at the time).

It is important to note that these estimates apply only to the most selective colleges and universities. Espenshade and Radford's (2009) data set contained only seven selective, 4-year colleges or universities. Kane's (1998) data set came from an analysis of the top 20% of 4-year colleges in terms of selectivity. His models based on all 4-year colleges yield estimated weights one-third as large. Such findings are in keeping with the patterns in Figure 1 that suggest there is greater use of race-based affirmative action at the most selective colleges.

Even taking into account the fact that they are based on a limited set of colleges, the Kane (1998) and Espenshade and Radford (2009) SAT-equivalent weight estimates are likely too high. Their models include a number of control variables, such as high school GPA and extracurricular involvement. Because these variables are positively correlated with SAT scores, their inclusion in the model will tend to attenuate the coefficient on the SAT score variable. This, in turn, will exaggerate the SAT-equivalent weight (because it is a ratio of the coefficient on race to the coefficient on SAT scores). Another way to see this is to realize that two students who differ by 300–400 SAT score points will tend to differ also on many other factors that affect college admission, so the average difference in admission probabilities between two students who differ by 300–400 SAT points will be much larger than that implied by the SAT coefficient alone. This means that a smaller difference in SAT points (along with the other differences in correlated characteristics) will yield an average difference in admission probability equal to that implied by the race coefficient.

Because of these concerns, and because existing estimates do not describe the weight that colleges give to Hispanic students or to low-SES students, we conducted our own simple analysis of recent college admission data. Using data from the 2002 ELS, a study that includes college application and admission data for a nationally representative sample of students who were 10th graders in 2002, we estimated racial and SES admissions weights using methods similar to those of Espenshade and Radford (2009) and Kane (1998). We fit a much more parsimonious model than they do, however: we predict the probability of admission using only test scores and dummy variables for race or a standardized variable for SES.[10] To account for the possibility that the implicit weights vary in magnitude along with the selectivity of the college, we repeated this analysis for admission to each of the six Barron's selectivity categories.

Similar to Kane (1998), we find notable racial admissions preferences only in the top Barron's category, which represents approximately 10% of 4-year colleges that are not open admission. We estimate significant positive admissions preferences for both Black and Hispanic students applying to these most selective colleges. We estimate that Black and Hispanic students are given an implicit weight that is roughly equivalent to that given to students with a test score roughly 1.3 standard deviations higher than another student. We find very little or no evidence of racial preferences in admissions to colleges in lower selectivity tiers (for details, see Table B1).

We conducted a similar analysis to estimate the average implicit weight given to low-SES students in admissions. Here we find evidence of slight SES-based affirmative action in the most selective colleges (the weight given to a standard deviation difference in family SES is roughly the same as given to a 0.15 standard deviation test score difference). Moreover, the evidence indicates that students applying to less selective colleges were penalized for their lower SES in the admission process (in these colleges higher SES students were given implicit preference in admissions). The SES weights are, however, relatively small in all cases (for details, see Table B2).

In sum, it appears that, in 2004, affirmative action or other related policies at the most selective colleges increased the probability of minority students' admission substantially by an amount that may be as high as the difference between students whose academic records differ by over a standard deviation. SES-based affirmative action policies, however, appear to have been much less prevalent. On average, low-SES applicants appear to have received little or no admissions preference at most colleges.

Table B1 Estimates of Implicit Weight Given to Minority Students in Admissions Process, High School Class of 2004

	All schools	Barron's 4	Barron's 3	Barron's 2	Barron's 1
SAT	0.076 ***	0.079 ***	0.09 ***	0.093 ***	0.115 ***
	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)
Asian	-0.004	-0.028	0.026	0.006	0.007
	(0.011)	(0.022)	(0.021)	(0.029)	(0.024)
	-5.26	*-35.44*	*28.89*	*6.45*	*6.09*
Black	-0.04 ***	-0.098 ***	-0.044 *	-0.028	0.303 ***
	(0.010)	(0.016)	(0.021)	(0.034)	(0.040)
	-52.63	*-124.05*	*-48.89*	*-30.11*	*263.48*
Hispanic	0.024 *	-0.025	0.01	0.037	0.294 ***
	(0.010)	(0.018)	(0.021)	(0.031)	(0.034)
	31.58	*-31.65*	*11.11*	*39.79*	*255.65*
Intercept	-0.015	0.038	-0.197	-0.376	-1.102
	(0.019)	(0.033)	(0.038)	(0.061)	(0.080)
N	23,000	6,700	5,000	2,800	2,700

Note. Authors' calculations from ELS 2002 study. Standard errors are adjusted for clustering. Estimates are from a linear probability model predicting acceptance to a given selectivity of school as a function of SAT score and dummy variables for race. SAT scores are divide by 100. Sample sizes have been rounded to the nearest 100. The implicit admissions weight (in SAT points) is included in italics below the standard error for each model.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B2 Implicit Weight Given to Socioeconomic Status (SES) in Admissions Process, High School Class of 2004

	All schools	Barron's 4	Barron's 3	Barron's 2	Barron's 1
SAT	0.076*** (0.002)	0.083*** (0.003)	0.092*** (0.003)	0.094*** (0.005)	0.09*** (0.006)
SES	0.01* (0.004) *13.2*	0.027*** (0.007) *32.5*	0.003 (0.008) *3.2*	0.001 (0.013) *1.1*	-0.033* (0.014) *-36.6*
Intercept	-0.025 (0.017)	-0.026 (0.030)	-0.216 (0.035)	-0.381 (0.057)	-0.716 (0.073)
N	23,000	6,700	5,000	2,800	2,700

Note. Authors' calculations from ELS 2002 study. Standard errors are adjusted for clustering. Estimates are from a linear probability model predicting acceptance to a given selectivity of school as a function of SAT score and the ELS socioeconomic status variable (continuous and standardized). SAT scores are divide by 100. Sample sizes have been rounded to the nearest 100. The implicit admissions weight (in SAT points) is included in italics below the standard error for each model.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix C: Detailed Explanation of Agent-Based Model Initialization

For each scenario of the model, we generate J colleges with m available seats per year (for the sake of simplicity, m is constant across colleges). During each year of the model run, a new cohort of N students engages in the college application process. Initial college quality (Q) is normally distributed, as are race-specific distributions of student achievement (A) and student resources (R). We allow for race-specific correlations between A and R. The values used for these parameters, and their sources, are specified in Table 1. We select these values to balance computational speed and distribution density (e.g., for number of colleges and students), real-world data (e.g., for achievement and resource distributions), and based on the original version of the model (ELS 2002; Reardon et al., 2014).

Submodels

Application. During this stage of our model, students generate an application portfolio, with each student selecting n_s colleges to which they will apply. Every student observes each college's quality (Q_c) with some amount of uncertainty (u_{cs}), which represents both imperfect information and idiosyncratic preferences.

$$Q_{cs}^* = Q_c + u_{cs}; \quad u_{cs} \sim N(0, \tau_s). \tag{C.1}$$

The error in students' perceptions of college quality has a variance that depends on a students' resources; students from high-resources families have better information about college quality. Specifically,

$$\tau_s = \mathrm{Var}(Q_c)\left(\frac{1-\rho_s^Q}{\rho_s^Q}\right), \tag{C.2}$$

where ρ_s^Q, the reliability of student perceptions of college quality, is a function of student resources and bounded between 0.5 and 0.7, as described in Table 1.

Students then use perceived college quality (Q_{cs}^*) to evaluate the potential utility of their own attendance at that college (U_{cs}^*), based on how much utility they place on college quality:

$$U_{cs}^* = a_s + b_s(Q_{cs}^*), \tag{C.3}$$

where a_s is the intercept of a linear utility function and b_s is the slope. Reardon et al. (2014) showed that allowing a_s and b_s to vary with students' socioeconomic resources had little effect on college application decisions; as a result we fix both to be constant across students.

Students may augment their own achievement, and they perceive their own achievement with noise. Thus, their assessment of their achievement, for purposes of deciding where to apply, is

$$A_s^* = A_s + \alpha_s + e_s; \quad e_s \sim N(0, \sigma_s), \tag{C.4}$$

where α_s represents enhancements to perceived achievement that are unrelated to achievement itself (e.g., strategic extracurricular activity participation or application essay consultation) and e_s represents a student's error in his or her perception of his or her own achievement. The values that are used for these parameters and their relationships with student resources are listed in Table 1. As above, the error in a student's assessment of his or her own achievement has a variance that depends on his or her family resources:

$$\sigma_s = \mathrm{Var}(A)\left(\frac{1-\rho_s^A}{\rho_s^A}\right), \tag{C.5}$$

where ρ_s^A, the reliability of student perceptions of their own achievement, is a function of student resources and bounded between 0.5 and 0.7, as described in Table 1.[11]

Based on their noisy observations of their own achievement and college quality, students estimate their probabilities of admission into each college:

$$P_{cs} = f(A_s^* - Q_{cs}^*), \tag{C.6}$$

where f is a function based on admission patterns over the prior 5 years. In each year f is estimated by fitting a logit model predicting the observed admissions decisions using the difference between (true) student achievement and college quality for each submitted application over the past 5 years. We set the intercept to 0 and the slope to $\beta = -0.015$ for the first 5 years of our simulation (since there are no prior estimates to use). These values were selected based on observing the admission probability function over a number of model runs; the starting values do not influence the model end-state, but do influence how quickly the function (and the model itself) stabilizes.

Each student applies to a set of n_s colleges, where n_s is determined by the student's resources, as described in Table 1. Given n_s, a student applies to the set of n_s colleges that maximize his or her overall expected utility. To determine the expected utility of an application portfolio, we do the following. Let $E_s^*\{C_1, C_2, \dots, C_{n_s}\}$ indicate student *s*'s expected utility of applying to the set of n_s colleges $\{C_1, C_2, \dots, C_{n_s}\}$, where the colleges in the set are ordered from highest to lowest perceived utility to student s: $U_{C_1 s}^* \geq U_{C_2 s}^* \geq \cdots \geq U_{C_n s}^*$. Define $E_s^*\{\emptyset\} = 0$. Let P_{cs}^* indicate student *s*'s perceived probability of admission to college *c*. Then the expected utility of applying to a given set of colleges is computed recursively as

$$E_s^*\{C_1, C_2, \dots, C_{n_s}\} = P_{C_1 s}^* \cdot U_{C_1 s}^* + \left(1 - P_{C_1 s}^*\right) \cdot E_s^*\{C_2, \dots, C_{n_s}\}. \tag{C.7}$$

In our model, each student applies to the set of colleges $\{C_1, C_2, \dots, C_{n_s}\}$ that maximizes $E_s^*\{C_1, C_2, \dots, C_{n_s}\}$. In principle, this means that a student agent in the model computes the expected utility associated with applying to every possible combination of three colleges in the model and then chooses the set that maximizes this expected utility. The model developed by Reardon et al. (2014) uses a fast algorithm for this maximization; we use the same algorithm here.

Although the model assumes all students are rational, utility-maximizing agents with enormous computational capacity, this is moderated by the fact that the student agents in the model have both imperfect information and idiosyncratic preferences, both of which are partly associated with their family resources. This means that there is considerable variability in student application portfolios, even conditional on having the same true academic records, and that high-resource students choose, on average, more optimal application portfolios than lower-resource students. Both of these features mimic aspects of actual students' empirical application decisions (e.g., Hoxby & Avery, 2012). More generally, the assumption of rational behavior is an abstraction that facilitates focus on the elements of college sorting that we wish to explore. We recognize that real-world students use many different strategies to determine where they apply.

Admission. Colleges observe the apparent achievement $(A_s + \alpha_s)$ of applicants with some amount of noise (like the noise with which students view college quality, this also reflects both imperfect information as well as idiosyncratic preferences):

$$A_{cs}^{**} = A_s + \alpha_s + w_{cs}; \quad w_{cs} \sim N(0, \Phi). \tag{C.8}$$

As described in Table 1, colleges assess students' achievement with a reliability of 0.8. Given that true achievement has a variance of 200^2 in the population, this implies that the error variance colleges' assessments of student achievement is

$$\phi = \mathrm{Var}(A)\left(\frac{1-0.8}{0.8}\right) = .25 \cdot 200^2 = 100^2. \tag{C.9}$$

Thus, in the model, colleges' uncertainty and idiosyncratic preferences have the effect of adding noise with a standard deviation of 100 points (half a standard deviation of achievement) to each student's application.[12]

Affirmative action policies are activated after year 15 of model runs (in order to allow college quality and application, admission, and enrollment behavior to stabilize first). At this point, colleges' binary affirmative action statuses (S_c)—which had previously all been 0—are set and remain stable through the remainder of the model run. Perceived student achievement adjusted by model-specific race affirmative action (G) and resource affirmative action (H) magnitude values is given by:

$$A_{cs}^{***} = A_{cs}^{**} + S_c[G \cdot (Black_s | HIspanic_s) + H \cdot R_s]. \tag{C.10}$$

Colleges rank applicants according to A_{cs}^{***} and admit the top applicants. In the first year of our model run, college's expected yield (the proportion of admitted students that a college expects to enroll) is given by:

$$Yield_c = 0.2 + 0.6(College\ quality\ percentile), \tag{C.11}$$

with the lowest-quality college expecting slightly over 20% of admitted students to enroll and the highest quality college expecting 80% of admitted students to enroll. In subsequent years, colleges admit $m/Yield_c$ students in order to try to fill m seats (where $m = 150$ in our model). After the first year of a model run, colleges are able to use up to 3 years of enrollment history to determine their expected yield, with $Yield_c$ representing a running average of the most recent enrollment yield for each college.

Enrollment. Students enroll in the college with the highest estimated utility of attendance (U_{cs}^{*}) to which they were admitted.

Iteration. Colleges' quality values (Q_c) are updated based on the incoming class of enrolled students before the next year's cohort of students begins the application process:

$$Q_c' = 0.9(Q_c) + 0.1(\bar{A}_c), \tag{C.12}$$

where $\bar{A}_c$ is the average value of A_s among the newest cohort of students enrolled in college c. We run the model for 30 years. In our simulations, this is a sufficient length of time for the models to reach a relatively stable state.

Notes

[1] Barron's Profiles of American Colleges (http://www.barronspac.com) provides selectivity rankings for most 4-year colleges in the United States. Colleges are ranked on a scale from 1 (*most selective*) to 6 (*least selective*); colleges with a ranking of 7 are specialty colleges with unique admissions criteria. These rankings are based on the high school GPAs, high school class rank, and SAT/ACT scores of enrolled students, as well as the proportion of applicants admitted. To give a concrete example, colleges ranked in the top two categories (1 and 2) in 2004 had median SAT scores of at least 575, admitted fewer than 50% of applicants, and enrolled students with median GPAs of about 3.5 and in the top 35% of their high school class.

[2] Under percent plans, any student who graduates in some prespecified top percentage of their high school class automatically gains admission to the public university system. In order to increase the racial diversity of university admissions, such plans leverage the existing racial segregation of high schools; any plan that takes the top portion of a school with a high minority population is bound to admit a sizeable number of minority students. Three public systems (the University of California, the University of Texas, and the Florida State University) have already enacted some version of a percent plan because of existing affirmative action bans or because of anticipation of future restrictions on race-conscious affirmative action. The extant research indicates that such plans tend to reduce racial and ethnic diversity relative to the affirmative action plans that preceded them (Arcidiacono & Lovenheim 2014; Bastedo & Jaquette, 2011; Howell, 2010; Long, 2004, 2007), and it was the legal challenge of Texas's attempt to increase its universities' diversity above and beyond what their percent plan yielded that led to the *Fisher* case.

[3] The difference between a posthoc inference of the average weight given to race and assigning a numerical value to race in an admissions process is subtle but important. To see the difference, consider a baseball team that would like players who can play a range of positions and would also like each of them to be skilled hitters (e.g., having a high on-base percentage). If the pool of potential players includes a large number of fielders who are great hitters but few pitchers who are good hitters, the team may reasonably pass up a player who is an excellent fielder and hitter in order to sign a pitcher who is a weaker hitter because it needs some great pitchers. If one then compared the average predraft on-base percentages of pitchers and fielders to measure the "weight" assigned to being a pitcher in the signing process, this difference would likely be large—maybe 200 points. But this does not mean the team added 200 points to each pitcher's observed predraft on-base percentage and then simply signed the players with the on-base percentage, regardless of whether they were fielders or pitchers.

[4] We base the population data in the simulation on the nationally representative sample of students in the ELS conducted by the National Center for Education Statistics. These students and their parents were surveyed and tested beginning in 2002, when the students were in 10th grade. The achievement distribution is based on the standardized assessment of English language arts and mathematics given to that

sample in 10th grade. The family resource dimension is based on the ELS SES index, a composite measure of mother's and father's education, mother's and father's occupation, and family income. This measure captures the dimensions of class proposed by Kahlenberg (1996) for use in class-based affirmative action policies.

[5] Although 100% of students in our model apply to colleges, roughly 40% don't get in anywhere because there are fewer seats than students. An alternative model would have students with near-zero probabilities of admission not apply to any colleges. Our results are not sensitive to this modeling choice, however, because these students' applications have no aggregate effect on what type of students are admitted to colleges—the colleges in our model end up with the same students using either approach.

[6] For a more detailed explanation of the agent-based model, see Appendix C.

[7] The six versions of affirmative action (AA) policies are (a) no racial AA and moderate SES AA, (b) no racial AA and strong SES AA, (c) moderate racial AA and no SES AA, (d) strong racial AA and no SES AA, (e) moderate racial AA and moderate SES AA, and (f) strong racial AA and strong SES AA.

[8] This is not to say that the correlation isn't high—it is—however, it is not high enough that one can be used as a proxy for the other in affirmative action policies. This conclusion is consistent with the ineffectiveness of SES-based K–12 school integration policies at producing racial integration (Reardon et al., 2006; Reardon and Rhodes, 2011).

[9] This may seem counterintuitive, but it results from the fact that racial differences in mean test scores mean that there are more minority students with very low scores and more White students with very high scores. If a college simply admitted every student with an SAT score above, say, 1200, the mean score for White students in this group would be higher than that of minority students because of the higher proportion of White students with very high scores.

[10] In these analyses, we use SAT scores, which are reported in the ELS data, as a standardized test score measure. We use them because they are widely observable to colleges (unlike the tests administered as part of the ELS study) and they are standardized on a common scale (unlike GPA). Although colleges of course have access to other information about students when making admissions decisions, we use a single standardized test score measure as a unidimensional proxy for students' academic performance so that we can roughly quantify the implicit weights given to race or SES in college admissions. The weights we estimate therefore should be understood as designed solely to provide information about the rough order of magnitude of the weights given to academic performance, race, and SES in admissions processes. They are not particularly useful as estimates of actual admissions processes.

[11] The intercept value, minima, maxima, and linear relationships with resources used for the reliabilities with which students perceive their own achievement and college quality, as well as the intercept and slope values used for students' evaluation of the utility of

attending colleges, are based on those used in previous work (Reardon et al., 2014). Briefly, the resource relationships are based on experimentation into the role of differential information quality in the observed sorting of students into colleges by SES (Reardon et al., 2014). In the absence of available empirical evidence, the other values used are plausible estimates: The average student has moderately high, but not perfect, perception of college quality (e.g., familiarity with college rankings) as well as his or her own achievement (e.g., knowledge of their SAT scores); because of resource, effort, and opportunity costs the utility of attending a very low-quality college is less than 0 (i.e., lower than not attending college). Extensive model testing suggests that our selections of these specific parameter values did not affect the overall interpretation of our results.

[12] As with the parameter values that describe student perception, the means, minima, and maxima used for the reliability with which colleges perceive student achievement is based on what was used in previous work (Reardon et al., 2014). Although there is a lack of extant empirical evidence to inform these values, we made estimates that seem sensible: collectively, college admission officers have quite a bit of experience evaluating students and thus colleges have a highly accurate (but also not perfect) perception of student achievement. Extensive model testing suggests that our selections of these specific parameter values did not affect the overall interpretation of our results.