Stanford cepa | Center for Education Policy Analysis

CEPA Working Paper No. 15-04

What Levels of Racial Diversity can be Achieved with Socioeconomic-Based Affirmative Action? Evidence from a Simulation Model

AUTHORS

Sean F. Reardon
Stanford University

Rachel Baker
University of California, Irvine

Matt Kasman
Brookings Institution

Daniel Klasik
George Washington University

Joseph Townsend
Stanford University

ABSTRACT

This paper investigates to what extent socioeconomic status (SES)-based affirmative action in college admissions can produce racial diversity. Using simulation models, we investigate the racial and socioeconomic distribution of students among colleges under the use of race- or SES-based affirmative action policies, and/or targeted, race-based recruitment policies. We find, first, that neither SES-based affirmative action nor race-targeted recruiting on their own produce levels of racial diversity achieved by race-based affirmative action. However, the two policies in combination, although likely expensive, may yield racial diversity comparable to race-based affirmative action. Second, the use of affirmative action policies by some colleges reduces the diversity of similar-quality colleges without such policies. Third, the combination of SES-based affirmative action and race recruiting results in fewer academically-overmatched Black and Hispanic students than under race-based affirmative action, but the schools that use both also see a reduction in the academic achievement of enrolled students.

VERSION

December 2017

Suggested citation: Reardon, S.F., Baker, R., Kasman, M., Klasik, D., & Townsend, J.B.. (2017). What Levels of Racial Diversity can be Achieved with Socioeconomic-Based Affirmative Action? Evidence from a Simulation Model (CEPA Working Paper No.15-04). Retrieved from Stanford Center for Education Policy Analysis: http://cepa.stanford.edu/wp15-04

What Levels of Racial Diversity can be Achieved with Socioeconomic-Based Affirmative Action?

Evidence from a Simulation Model

Sean F. Reardon*
Rachel Baker**
Matt Kasman+
Daniel Klasik++
Joseph B. Townsend*

Version: November 2017

Forthcoming, *Journal of Policy Analysis and Management*

*Stanford Graduate School of Education

** University of California, Irvine - School of Education

+ Brookings Institution

++ The George Washington University

Corresponding author: Sean F. Reardon, e-mail: sean.reardon@stanford.edu.

This paper was supported by the Network on Inequality, Complexity, and Health, funded by the National Institutes of Health (NIH) Office of Behavioral and Social Sciences Research (OBSSR) (Award HHSN276200800013C) and by the Educational Testing Service (ETS). We appreciate the advice of Elizabeth Bruch, Rucker Johnson, Gary Orfield, Mark Long, and Ross Hammond on earlier versions of this paper. The views expressed here, however, are our own and do not reflect the views of either NIH or ETS.

What Levels of Racial Diversity can be Achieved with Socioeconomic-Based Affirmative Action? Evidence from a Simulation Model

Abstract

This paper investigates to what extent socioeconomic status (SES)-based affirmative action in college admissions can produce racial diversity. Using simulation models, we investigate the racial and socioeconomic distribution of students among colleges under the use of race- or SES-based affirmative action policies, and/or targeted, race-based recruitment policies. We find, first, that neither SES-based affirmative action nor race-targeted recruiting on their own produce levels of racial diversity achieved by race-based affirmative action. However, the two policies in combination, although likely expensive, may yield racial diversity comparable to race-based affirmative action. Second, the use of affirmative action policies by some colleges reduces the diversity of similar-quality colleges without such policies. Third, the combination of SES-based affirmative action and race recruiting results in fewer academically-overmatched Black and Hispanic students than under race-based affirmative action, but the schools that use both also see a reduction in the academic achievement of enrolled students.

What Levels of Racial Diversity can be Achieved with Socioeconomic-Based Affirmative Action? Evidence from a Simulation Model

In its 2013 *Fisher v. University of Texas at Austin (Fisher I)* decision, the Supreme Court upheld the concept of race-conscious 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). After the Fisher case returned in 2015, the Court again emphasized the need for “regular evaluation of data” to ensure “that race plays no greater role than is necessary” (*Fisher v. University of Texas at Austin (Fisher II)*, 2016, p. 11). Both decisions 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 would continue to be necessary to achieve that goal. This paper answers that question.

It seems clear that no obvious proxy for race could ever fully replicate the racial diversity achieved using race explicitly in the admissions process—each alternative would necessarily be a noisy measure of race and so a less efficient means of selecting a racial diverse set of students. However, in addition to percent plans, there are two potential race-neutral alternative admissions policies that might yield racial diversity at selective universities have been explored. These are affirmative action based on socioeconomic status (SES) rather than race, and recruitment efforts that target underrepresented racial minority students. Such policies would avoid the constitutional challenge of relying on race to determine admission, but can they produce sufficient racial diversity to satisfy universities’ legitimate educational interests?

This question is, of course, hypothetical. Few colleges, for example, currently use affirmative action based on SES in any substantial way. As a result, standard methods for evaluating existing policies cannot determine 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. Thus, 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 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 can 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 not definitive about what would actually happen under a given policy, they can describe patterns of likely outcomes under assumptions derived from other research and can provide guidance regarding the probable effectiveness of different types of policies.

With these aims in mind, this article uses a simulation model to investigate the dynamic effects of various types of affirmative action admission policies on campuses' racial diversity and on the average academic achievement of students, both at schools that use these policies and those that do not. We also examine a common claim made by opponents of affirmative action: that students admitted under such plans are academically out-matched by their peers.

Current patterns of racial diversity at selective colleges and universities

Any race-neutral affirmative action approach faces a serious challenge. Even with the legality of race-conscious affirmative action policies, Black and Hispanic students remain underrepresented in higher education, particularly at selective institutions. Very selective colleges (those colleges with Barron's selectivity ratings 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. Appendix A includes a comparable figure describing the income composition of postsecondary institutions where we see lower-income students are likewise underrepresented at more selective colleges (see also Chetty, Friedman, Saez, Turner, & Yagan, 2017).

[Figure 1 here]

In general, Black and Hispanic enrollment is lower in selective colleges and universities. The most selective colleges, however, are slightly more racially diverse than those just below them in the selectivity rankings. This difference may be partially the result of race-based affirmative action policies used by some of these most selective colleges. It may also result from the additional sources of financial aid available that more selective colleges can use to support a more diverse class of students (Hoxby & Avery, 2012). Although we do 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 percent Black or Hispanic students, much lower than the 30 percent Black and Hispanic individuals comprise in the overall population of 18-year-olds.

Existing research on the effects of affirmative action support these hypotheses. Evidence of affirmative action is most visible at selective, state-flagship universities (Backes, 2012; Brown & Hirschman, 2006; Hinrichs, 2012; Long, 2007). The elimination of affirmative action policies in some states has resulted in drops in the enrollment of Black and Hispanic students at these schools (Backes,

[1] Barron's Profiles of American Colleges (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*). 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. Colleges ranked in the top two categories (1 and 2) in 2004 had median SAT® scores of at least 575, admitted fewer than 50 percent of applicants, and enrolled students with median GPAs of about 3.5 and in the top 35 percent of their high school class.

2012; Brown & Hirschman, 2006; Dickson, 2006; Hinrichs, 2012; Long, 2007). Some of this enrollment drop may be attributable to a decline in applications, perhaps because underrepresented minority (URM) students interpret these bans as a signal that they are not welcome (Brown & Hirschman, 2006; Dickson, 2006).

Race-neutral affirmative action policies

Some state university systems have responded to legislated bans on affirmative action either through increased recruitment of underrepresented students. The University of Washington, for example, was able to recover from a drop in applications from URM students with proactive recruitment (Brown & Hirschman, 2006). California, in response to Proposition 209, saw less successful results from a similar strategy (Gándara, 2012). Recruitment efforts work in part by making students aware of specific colleges and by making these colleges seem more appealing to prospective students through additional, targeted contact with those students (Gurantz, Hurwitz, & Smith, 2017). Texas took efforts to make its campuses seem more appealing to underrepresented students one step further and, in addition to special recruitment and academic support programs, offered two special scholarships for enrollment in the Texas flagship universities to students from high schools in low-income areas with a low college-going tradition (Andrews, Imberman, & Lovenheim, 2016; Niu & Tienda, 2010). Only one of these programs increased enrollment among targeted students (Andrews, et al., 2016).

Often, targeted recruitment is paired with "percent plan" admissions policies. Under percent plans, any student who graduates in some pre-specified top percentage of their high school class automatically gains admission to the public university system. Such plans leverage the existing racial segregation of high schools to increase the racial diversity of university admissions. Indeed, any plan that takes the top portion of a school with a high minority population is likely to admit a sizeable number of minority students from that school. Percent plans have been implemented in the three largest states—

California, Texas, and Florida. Evaluations of these policies indicate that they have not been effective at maintaining racial diversity levels after state-wide bans on race-conscious affirmative action (e.g., Arcidiacono & Lovenheim, 2014; Bastedo & Jaquette, 2011; Horn & Flores, 2003; Lim, 2013; Long, 2004, 2007).

The failure of percent plans to deliver on their promise has 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 because of their race or ethnicity. The presumption is that such plans capitalize on the relationship between race and income in order to construct a socio-economically and 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 URM enrollment while simultaneously 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, at least without combining it with some form of race-awareness (Bowen, Kurzweil, & Tobin, 2005; Carnevale & Strohl, 2010; Espenshade & Radford, 2009; Kane, 1998; Long 2015; Reardon & Rhodes, 2011; Reardon, Yun, & Kurlaender, 2006; Xiang & Rubin, 2015). 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 and the ways that schools consider SES in admissions decisions vary widely (Espenshade & Radford, 2009; Gaertner & Hart, 2013).

Our aim in this paper is to, first, develop general intuition about SES-based affirmative action and how the racial diversity it achieves—alone or in combination with race-based recruiting—compares to the levels of racial diversity evident in selective colleges under current admissions practices. 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. For example, application patterns changed in Texas after the introduction of the state's percent plan: non-flagship public universities in Texas saw an increase in the average test scores of their applicants. These changes were likely due to changes in application behavior of high-scoring students who were not eligible for automatic admission on the basis of their class rank (Long & Tienda, 2010). Our aim is to expand such findings to examine how race- and SES-based affirmative action—arguably less-transparent than percent plans—might change application and enrollment patterns both at schools that use those policies *and* those that do not. Our simulations here provide insight into these potential system-wide, dynamic effects of affirmative action admissions policies.

Finally, some critics of race-based affirmative action claim that it does a disservice to URM students because it places them in environments where their academic preparation systematically falls below that of their peers (e.g., Arcidiacono, Aucejo, Coate, & Hotz, 2014; Arcidiacono & Lovenheim, 2005; Sander, 2004). This mismatch might lead to within-college racial segregation based on academic background or a lower likelihood that URM 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 URM students in colleges where their achievement falls substantially below their peers.

The utility of agent-based simulation

We build intuition about the effects of different admissions policies using an agent-based model (ABM) that is grounded in real-world data and that incorporates a complex (though highly stylized) set of features of the college application, admission, and enrollment processes. Our model relies on a synthetic world of students and colleges created to mimic the salient characteristics of students and colleges in the real world. We give these actors rules to engage independently in a process that simulates college admissions in the real world. By using an ABM, we can 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. Our model supports the investigation of how diversity boosting policies might affect university composition in a world in which *students* (a) have idiosyncratic preferences about colleges, (b) have 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.

Many, but not all, of these features are present in previous, structural models of the college admissions process (for example, Fu, 2014; Howell, 2010). However, agent-based modeling in general, and our model design in particular, are well-suited for answering the policy questions that we address because we can observe behavior and outcomes for specific students and colleges at any given point in time. Although our model falls short of being completely realistic, it captures important, dynamic features of the application/ admissions/ enrollment processes that enable the investigation of the ways that affirmative action might affect enrollments.

In addition, an important assessment of the validity of an ABM is whether it has “generative sufficiency;” whether it can reliably produce meaningful, macro-level outcomes similar to those observed in the real world given a set of realistic input parameters and rules for micro-level behaviors (Epstein, 1999). Reardon, Kasman, Klasik, and Baker (2016) demonstrate that a model with the stylized dynamics that we incorporate meets this condition and can replicate realistic patterns of application and enrollment.

This simulation approach improves upon previous assessments of race and SES-based affirmative action in several important ways. First, unlike prior simulations, it models a dynamic system of students and colleges, rather than relying on static, regression-based or structural models. Nearly all previous studies of SES-based affirmative action have been based on simulations where regression-based estimates of race- or legacy-based admissions boosts are simply added to the academic qualifications of low income students from the original data to create a new hypothetical class of admitted students (Bowen, Kurzweil, & Tobin, 2005; Carnevale & Strohl, 2010; Espenshade & Radford, 2009).

Second, many of the studies that model application and admissions decisions have not directly addressed the potential of SES-based affirmative action, (Arcidiacono 2005; Howell 2010; Long 2015). Arcidiacono (2005) and Howell (2010) use structural models of the college enrollment process to examine the effect of changes in affirmative action policies on college enrollment choices (Howell, 2010) and future earnings (Arcidiacono, 2005). None of the simulations, however, include SES-based affirmative action. Alternatively, Long (2015) simulates changes in college diversity if colleges could give admissions boosts to students based on predictions of a student's race according to observable characteristics other than race, including measures of SES. Although these studies model application and admissions decisions explicitly, they too hinge on simply removing or adding various regression-estimated advantages to URM (or expected-URM) students in college admissions decisions.

Third, none of these approaches provide intuition on how application and admission behavior might change in *response* to the simulated outcomes of the changes in policy. This is not a trivial omission. We know that, for example, UT Austin has had to add a cap to the number of students it admits under the Texas percent plan because demand for seats at the school is so high under the percent plan policy—a response that could not be modeled with structural approaches of prior affirmative action research. Although we establish certain parameters of our model in similar ways to earlier models (such as estimating the size of the admission boost that might be appropriate to use for an SES-based admission policy), repeated simulations in our model allow student and college behavior to adapt in response to different admission policies and the resulting changes in the size and composition of enrolling cohorts of students.

Fourth, previous simulation studies are limited by the generalizability of their claims because of the data they use. For example, some are based on relatively small subsets of the postsecondary system ranging from a single state university (Gaertner & Hart 2013), to a single state system (Long 2015; Long & Tienda, 2010), to the 193 "most selective" colleges (Carnevale & Strohl 2010). This focus makes sense when the goal is to understand how admissions policies affect admission and enrollment patterns at particular types of schools, but it is not clear how far these results generalize to other institutions. Other simulations are based on more complete national data, but these data are usually old and likely unable to speak to more recent trends in college choice. For example, Howell (2010) uses data from the high school class of 1992, while Arcidiacono (2005) uses data from the class of 1972. Our simulated system includes 40 simulated institutions, but—along with the students in our simulation—they are constructed to represent the full system of degree-granting colleges and universities and the national population of high school students and is based on parameter estimates from 2004 and later.

Finally, our simulation approach is more realistic than other simulations in some important ways. For example, whereas the simulation in Carnevale and Strohl (2010) assumed that all students apply to all colleges, our model, like Howell (2010), has students strategically applying to a small portfolio of colleges based on their (imperfect) assessments of both college quality and their likelihood of admission. Moreover, in the Carnevale and Strohl (2010) 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 college-specific 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 achievement of an applicant is assessed across a host of dimensions and one college's assessment of the contribution of a student to the campus population might differ from another college's assessment of the same student.

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 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. However, a nonzero answer to this question does not 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.

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. A common strategy is to use data from a pool of applicants to one or more selective colleges to predict admission on the basis of race, academic, and other observable factors like SAT® exam scores and then compare the coefficients on the race variables with the coefficient on SAT® scores (see, for example, Kane, 1998 and Espenshade & Radford, 2009). For example, if a Black student's probability of admission were 7 percent greater than an otherwise observationally identical White student, one can calculate what change in SAT® exam score would be needed to yield the same 7 percent boost in the probability of admission. We review these prior studies in some detail in Appendix B. Due to our concerns that the race weights estimated in these studies are likely too high, and because existing estimates do not describe the weight that colleges give to Hispanic students or to low-SES students, we also conduct our own simple analysis to estimate the relative weights given to race, SES, and academic performance in selective college admissions.

Using data from Educational Longitudinal Study of 2002 (ELS), we estimate racial and SES admissions weights using a much more parsimonious version of the model fit by Espenshade and Radford (2009) and Kane (1998). We predict the probability of admission using only test scores and dummy variables for race or a standardized variable for SES.[2] 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 colleges in each of the six Barron's competitiveness categories.

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 the 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 preferences for Black or Hispanic students in admissions to colleges in lower selectivity tiers and we find no evidence that Asian students are given any additional admissions weight in any selectivity tiers (see Appendix Table B1).

We find evidence of slight SES-based affirmative action in the most selective colleges—a standard deviation difference in family SES is roughly the same as a 0.15 standard deviation difference in academic record. However, lower-SES students applying to less selective colleges appear to be penalized in the admission process. In these colleges higher SES students were given implicit preference in admissions decisions. The SES weights are relatively small in all cases. This heterogeneity perhaps reflects 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 (see Appendix Table B2).

[2] In these analyses, we use SAT® scores 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 have access to other information about students, we use a single test score measure as a unidimensional proxy for students' academic performance. 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.

These findings suggest that race-based affirmative action plays (or played, in 2004) some role in admissions to highly selective colleges but SES-based affirmative action does not. We reiterate that our estimates 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

Model design

We use a modification of the agent-based model of college application, admission, and enrollment developed and described in depth by Reardon, Kasman, Klasik, and Baker (2016). The model includes two types of entities: students and colleges. We set up the model with 40 colleges and 10,000 new college-age students per simulated year.[3] Students have three characteristics: race, a measure of high school academic achievement, and a measure of family resources. The race-specific distributions of academic achievement and resources, and race-specific correlations between resources and academic achievement were based on the real-world relationships between these variables observed in ELS, a nationally representative sample of high school students who would graduate in 2004. The achievement distribution is based on the standardized assessments of English language arts and mathematics administered to that sample in 10th grade. The family resource dimension is based on a composite measure of a student's mother's and father's education, mother's and father's occupation, and family income generated by the National Center for Education Statistics. This measure captures the dimensions of class proposed by Kahlenberg (1996) for use in class-based affirmative action policies. The parameters

[3] We conduct separate draws for each student cohort within a simulation run for two reasons. The first is that this is a realistic approach, as student cohorts can be expected to differ from one another. The second is that by doing so we gain confidence that our results are not driven by the attributes of a specific set of students.

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 percent are Black, 20 percent are Hispanic, and 60 percent are White, similar to actual proportions of the college-age population. The academic achievement characteristic represents the academic qualities that make a student attractive to a college (e.g., test scores, GPA, high school transcripts). We converted the scores from the original ELS test score scale to one that approximates the 1600-point SAT® exam scale (mean 1000, standard deviation 200) because of the ubiquity of this scale in general as well as its use in existing literature on affirmative action policies. 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). The family resource measure is standardized to a mean of 0 and standard deviation of 1.

Based on the findings of Reardon et al. (2016) and described more formally below, we structured the model to allow students' family resources to influence the college application process in four ways. First, students' resources and academic achievement are positively correlated. Second, students with more resources submit applications to more colleges than their lower-resource peers. Third, students with higher resources have higher quality information both about college quality and their own academic achievement relative to other students. This information 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, visible to colleges as they make admissions decisions (analogous to engaging in test preparation or private tutoring, obtaining help writing college essays, or strategically participating in extracurricular activities). These features of the model are explained and calibrated in Reardon et al. (2016). Reardon et al. (2016) 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.

Each of the 40 colleges in our model 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 is roughly the same as the proportion of 2002 tenth graders who attended any type of college by 2006.[4] 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). Quality is operationalized as the three-year running average of 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, detailed fully in Appendix C. 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. They then select a limited number of colleges to which to apply based on their uncertain and somewhat idiosyncratic perceptions of the utility of attending each college and of their probability of admission to each. During this stage, the model can allow some colleges to use race-based recruitment strategies that enhance the perceived utility of attending those colleges for targeted students.

[4] Although all of the students in our model apply to colleges, roughly 40 percent of students are not admitted anywhere because there are fewer seats than students. An alternative would be to model non-application based on parameters estimated from student observables and noise. Our results are not likely to be sensitive to this modeling choice, however, for two primary reasons. First, the students that would not apply at all are likely to be drawn from the pool of students in our simulation that do not receive acceptance to any college: low achieving students with poor information. Of course, some high achieving students would also probably not apply. This second type of student is represented in our simulations as having idiosyncratic preferences for colleges. There are numerous examples of students with sufficiently high achievement to gain acceptance to some college that ultimately do not because they prefer a different set of schools. Second, our results primarily focus on the top 10 percent of colleges. These schools pull students from the upper end of the achievement distribution, where not applying to college is uncommon. In effect, the colleges in our model end up with very similar students using either approach.

More formally, a student decides where to apply based on his/her perception of his/her own academic achievement, the perceived quality of a college, the utility of attending a college, and an estimation of the likelihood the student will be admitted to a college. A student perceives his/her own achievement according to

$$A_s^* = A_s + b \cdot resources_s + e_s;\ \ e_s \sim N(0, \sigma_s),$$

where A_s^* is the student's estimate of how appealing she or he will be to colleges, A_s is the student's actual academic achievement, and $b \cdot resources_s$ represents the extent to which the student has enhanced his or her apparent academic achievement (e.g. via SAT® exam coaching or extracurricular participation). This enhancement parameter varies linearly with family resources. A student perceives his/her own academic achievement with some error, captured by e_s. This term also varies with family resources, such that students with more family resources perceive their academic achievement with less error (i.e., σ_s is inversely related to resources).

Students observe the quality of colleges according to

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

where Q_{cs}^* is student s's perception of college c's quality, Q_c is the actual quality of each college, and u_{cs} is a random noise term drawn from a normal distribution whose variance is again a function of the student's family resources. This noise captures idiosyncratic preferences for colleges (e.g., a student might be impressed by a college's dormitories or the tour guide) as well as imperfect information on the part of students. Higher resource students perceive quality with less noise—they have better information and more uniform preferences about college quality.

U_{cs}^* is the perceived utility of attending college *c* for student *s*. It is given by

$$U_{cs}^* = a_s + b_s(Q_{cs}^*) + R_{sc}.$$

Here a_s and b_s are the intercept and slope of a linear utility function. R_{sc} captures the result of race-targeted recruitment strategies on the part of colleges. This recruitment term is meant to represent the increase in perceived desirability of a college that has made special efforts to recruit Black and Hispanic students, whether through targeted visits to high-Black and -Hispanic high schools, strategic disbursement of financial aid, or other methods. R_{sc} is the increase in student *s*'s perception of the utility of college *c* that comes from recruitment of *s* by *c.* This enhanced utility value is used by students when making application and enrollment decisions.[5]

A student's estimation of her probability of admission to a given college *c* is given by

$$P_{cs} = f(A_s^* - Q_{cs}^*)$$

where f is a logit function predicting admissions outcomes using the difference between a student's true academic achievement and college quality for each submitted application over the prior 5 years.[6] Students apply to the set of colleges $C_1, C_2, \dots, C_{n_s}$ that maximizes $\mathrm{E}_S(C_1, C_2, \dots, C_{n_s})$, which can be calculated recursively as:

$$\mathrm{E}_S(C_1, C_2, \dots, C_{n_s}) = P_{C_i s} U_{C_i s}^* + (1 - P_{C_i s}) \mathrm{E}_s(C_1, C_2, \dots, C_{n_s} \backslash C_i).$$

This recursive approach is similar to the sequential utility maximization of application choices used by Howell (2010).

Although the model assumes all students are rational, utility-maximizing agents with enormous computational capacity, this rationality is moderated by the fact that the student agents in the model have both resource-related imperfect information and idiosyncratic preferences. This means that there is considerable variability in student application portfolios, even conditional on having the same true

[5] It may be that some students also have an explicit preference for racial diversity. The explicit modeling of this dimension of college choice is left for future work, however we can interpret a version of these preferences in the noisy perception of college quality.

[6] We also attempted a simulation in which students knew which colleges were using affirmative action policies, but the resulting movement of Black and Hispanic students into affirmative action colleges was quite substantial so we omitted this condition from our analyses. This decision is warranted because real students likely have a vague sense that affirmative action will help their admissions chances, however the specifics of exactly which colleges offer how much additional consideration is relatively opaque. Although scholars have documented reductions in URM applications to colleges that have banned race-conscious policies (Brown & Hirschman, 2006), we argue the explicit, often highly publicized, prohibition of a policy is much more salient for decision making than a vague awareness of its presence.

academic achievement, 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) and produce realistic patterns of application (Reardon et al., 2016).

In the *admission* stage, colleges observe the academic records of students in their applicant pools and admit those they (noisily) 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. In the calculation of how many students to admit, colleges consider the total number of seats they want to fill (150 in all cases) and a three-year running average of yield—the percentage of admitted students who enroll—and will admit as many students as they think they need to fill their seats exactly. Like students, colleges view the world with some uncertainty and idiosyncrasy. This means, for example, that colleges do not rank students identically, reflecting the reality that different colleges have different preferences for students.

Formally, a college's assessment of the admissions desirability of a given student is represented by

$$A_{cs}^{**} = A_s + b \cdot resources_s + w_{cs} + T_c[G \cdot (Black_s|Hispani\ \ _s) + H \cdot resources_s];$$

$$w_{cs} \sim N(0, 100^2).$$

That is, a college perceives the actual academic achievement of a student, A_s, plus any strategic enhancement of the student's academic achievement, $b \cdot resources_s$ (described above), with a certain amount of noise w_{cs}. The standard deviation of this noise term is half a standard deviation of the academic achievement scale, implying that colleges detect and consider students' academic achievement (including any enhancement effects) with a reliability of 0.8 (i.e. this noise reflects both a college's uncertainty and idiosyncratic preferences).

It is during the calculation of A_{cs}^{**} that colleges with an affirmative action policy apply additional weight to a student's perceived admissions desirability in accordance with that policy. This additional weight is captured by the term $T_c[G \cdot (Black_s|Hispanic_s) + H \cdot resources_s]$. In this term, T_c indicates whether a college has an affirmative action policy, G is the size of the race weight given to a student if they are either Black or Hispanic for colleges using race-based affirmative action (the same weight is given to both Black and Hispanic students). H is the size of the weight given to students under SES-based affirmative action policies, which is applied linearly in accordance with the student's resources, $resources_s$.

Finally, in the *enrollment* stage, students compare the colleges to which they have been admitted and enroll in the one with the greatest perceived utility (U_{cs}^*). At the end of each simulated year, each college's quality (or reputation) is updated by taking a weighted average of prior college quality and the average academic achievement of the newest cohort of enrolled students (where prior quality has a weight of 0.9 and the new cohort has a weight of 0.1). Likewise, colleges update their yield estimates with the three most recent years of admissions data. These three stages are repeated in the next year with a new draw of 10,000 students and the same set of colleges.

Model Application

We allow the model to run for 30 simulated years in two 15-year phases. Because the analytic focus is on simulation end states, and not trends, the simulation is not intended to represent 30 historical years. The first 15 years are a conservatively long burn-in period in which no college used any affirmative action policy. This burn in allowed the model to consistently settle into a state in which dynamic elements in the model (i.e. colleges' quality values, colleges' expected yield) are largely stable from one year to the next. After the 15-year burn-in period, specified colleges start to use affirmative action strategies, and the model then runs for an additional 15 years. Within five to eight years of using affirmative action strategies, college quality and enrollment patterns typically stabilize again (we discuss model stability in greater detail in Appendix C). We allow the model to run through year 30 and then use the average patterns of enrollment in the final five years (years 26 through 30) as our primary model output.

In order to explore the effects of different affirmative action and recruitment policies, we run our model under different policy scenarios. Each of these scenarios is defined by four parameters: the magnitude of race-based affirmative action, the magnitude of SES-based affirmative action, the magnitude of race-based recruitment, and the number and rankings of colleges that use affirmative action. To account for potential idiosyncrasies within a given simulation run—particularly acknowledging that a given solution may not be unique—we simulate each of the scenarios that we describe in our primary results ten times, and average across these ten runs to capture the college and student outcomes of interest that we present.

As stated above, most of the parameters in our model are estimated directly from the nationally representative ELS data. These parameters include the specification of the joint distribution of race, SES, and academic achievement, and the amount of additional weight given to URMs under race-based affirmative action. Other parameters, like the racial composition of the students in the model, the ratio of college seats to total students are approximations that are grounded in real-world data, but are abstracted away out of necessity (because, for example, we do not include race groups other than White, Black, Hispanic, and Asian) and simplicity. Parameters such as the selectivity of colleges and, consequently, students' assessments of their likelihood of admission, are determined by the model in accordance with the rules of the admissions process that the model dictates. As a result, they are accurate in the sense that they are the desired consequence of our agents responding to the model-defined system. Finally, some parameters, most notably the ones that give certain advantages to higher-resource students (like submitting more applications) were established and tested in Reardon et al. (2016).

Results

We start by presenting the levels of racial diversity produced by of various combinations of SES-based affirmative action and race recruiting relative to the racial diversity of our simulated colleges using a race-based affirmative action policy whose strength is equivalent to our estimate of the strength of such policies in the real world. For this portion of the analysis, we focus on the scenarios when the top ten percent of colleges—the four with highest quality—use affirmative action policies. In Figure 2 we present results from sixteen scenarios: no, light, moderate and strong SES-affirmative action (corresponding to an increase in admissions consideration of 0, 50, 100, and 150 achievement points for each decrease of one standard deviation in applicants' resources); no, light, moderate and strong race-based recruiting (corresponding to an increase in perceived college quality by 0, 25, 50, and 100 achievement points for prospective Black and Hispanic applicants); and all combinations thereof. In each cell, the light (dark) bar represents the proportion of Black (Hispanic) students enrolled in these four schools as a proportion of how many students enroll using the estimated real-world race-based affirmative action weight (weight of 260, results represented by the dotted line). As an example, in the third box from the left on the top colleges use "Strong" SES-based affirmative action and "Moderate" race-based recruitment resulting in nearly 80% of the Black student and over 100% of Hispanic enrollment, relative to race-based affirmative action. The specific proportions of each race group achieved under each policy are presented in Appendix Figure A2.

Increases in the strength of both policies increase the proportion of Black and Hispanic students relative to the baseline race-based policy. However, neither policy alone can recover the rates of Black and Hispanic enrollment we see using race-based affirmative action policies. To achieve these rates of diversity seen under our race-based policy, SES-based affirmative action and race recruiting need to be used at the strongest levels of our model. These simulations indicate that SES-based affirmative action and race recruiting together can replicate levels of racial diversity achieved by race-based policies, but it requires levels of SES-based affirmative action and race-recruiting that are quite large relative to current, observed admissions practices.

[Figure 2 here]

In Appendix Figures A3-A5, we present more detailed results showing the effects of SES-based affirmative action and race-based recruiting on the SES composition of schools (Figure A3), and the effects of race-based and SES-based affirmative action on the racial composition (Figure A4) and the SES composition (Figure A5) of schools. In short, they show similar findings to those presented in Figure 2, that SES-based affirmative action is not as effective as race-based affirmative action at generating racial diversity in the schools that use it unless it is used in conjunction with race recruiting (or race-based affirmative action itself). However, SES-based policies do create SES diversity in a way that race-based policies do not.

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 presence of such policies in other schools. Figure 3 illustrates these system dynamics—the effect of having the top four colleges using admissions policies (either SES-based affirmative action and race recruiting or race-based affirmative action) on the kinds of students (by achievement and race) enrolled in all colleges.[7] We present similar figures for the effects on achievement and proportion of low-resource students in Appendix D.[8] In both panels, black arrows indicate the colleges that use affirmative action and gray arrows show colleges that do not. Each of the arrows starts at the location in the figure corresponding to the racial composition and average high school academic

[7] In this and the following analyses we use the "strong" versions of SES-based affirmative action and race recruiting, as these were the only policies that in combination produce levels of racial diversity achieved under our race-based affirmative action simulation.

[8] We present the four college results because they are most analogous to patterns of affirmative action use in the real world. In Appendix D we present similar figures for the effects on Black and Hispanic and low-income enrollment of different numbers (four, ten, 20, and 40) of schools using affirmative action policies.

achievement of enrolled students in the college in the final year of the model's burn-in period (year 15), 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 (year 30), after some colleges in the model have been using admissions policies for 15 years.

[Figure 3 here]

A few results are immediately clear in Figure 3. First, colleges that use diversity-boosting admissions policies become more racially diverse and their students' average achievement declines. Second, the slope of this change is quite steep, indicating that the changes in mean achievement are much less pronounced than the changes in the proportion of Black and Hispanic students. Evident in these graphs, and even more evident in the graphs in Appendix D (which gives similar graphs for changes in income diversity as well as for scenarios in which more than 4 colleges use affirmative action policies) is that the less selective colleges that use affirmative action experience the greatest changes in both diversity and average achievement—their arrows are the longest. This pattern is especially true for schools that use SES-based affirmative action in combination with race recruiting.

Third, colleges that do not adopt affirmative action policies, but that are close in quality to those that do, also experience 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. This tradeoff may mean that a white student whose admission to a top-four college is on the margin, such that it is determined by whether they use race-based affirmative action, would enroll in colleges of similar quality regardless of whether affirmative action is employed.

Finally, the left-most arrow in each panel captures the characteristics of students in the model who end the process not enrolled in any college. In each panel, the introduction of diversity-boosting policies hardly moves these arrows. In other words, the margin of college attendance is generally unaffected by affirmative action policies and the characteristics of non-enrolled students remain mostly unchanged.[9]

Beyond the college-level consequences of affirmative action, we are also concerned with whether and how affirmative action policies affect the difference in academic achievement between the enrolled students and their peers. Figures 4 and 5 show mean academic achievement of Black and Hispanic students' college classmates as a function of Black and Hispanic students' own achievement, and affirmative action type. As an example of how to read these figures, consider Black and Hispanic students with achievement of 1300 in Figure 4. These students, when there is no affirmative action policy (solid black line), are enrolled in colleges where the mean achievement of their peers is roughly 1225. In scenarios with race-based affirmative action using estimated real-world levels, these same students attend colleges where the mean peer achievement level is roughly 1280 (black, dashed line). Analogous figures for White students are given in Appendix Figures E1 and E2.

The 45-degree line in these figures indicates when a student's own achievement is equal to the average achievement of his or her peers. This line can be used as a heuristic for considering college match: when the simulation results are above the 45-degree line, students are enrolled in colleges where their own achievement is below the mean peer achievement. The opposite is true when the lines are below the 45-degree line: in this case, students are enrolled in colleges where their own achievement is greater than the mean peer achievement. The closer the simulation lines are to the 45-degree line the closer the simulated policy, on average, sorts students into colleges with similarly achieving students. Note that while we discuss college match generally, we note that there must always be students that fall below the average achievement of their peers and determining when this mismatch is extreme enough that it leaves students academically disadvantaged is beyond the scope of this paper.

In Figure 4, only the top four colleges in the simulation use affirmative action or race recruiting.

[9] In Appendix D, we show that this is true up until more than half of colleges use targeted admissions policies, then the population of students not enrolled in college includes notably fewer Black and Hispanic students and has higher mean achievement.

We present effects of these policies on Black and Hispanic students enrolled in all colleges, because, as we just demonstrated, policies enacted at one college can affect enrollment across the system.

[Figure 4 here]

We start by considering the two baseline simulations: no affirmative action policy, and race-based affirmative action with estimated real-world weights. Under no affirmative- action Black and Hispanic students with achievement above roughly 1150 attend colleges where their own achievement is 50-70 points *higher* than that of their peers. This is among the largest gaps observed between own achievement and peer achievement, and stands in contrast to the race-based policy, where the results hew most closely to the 45-degree line of all the policy simulations. This suggests that Black and Hispanic students, race-based affirmative action generates the closest overall match between own achievement and peer achievement. Given this relationship, it worth noting that the no-affirmative-action simulation line crosses the 45-degree line lower in the achievement distribution, at about 1050 compared to roughly 1150 for the race-based simulation, meaning fewer students would find themselves below the mean achievement of their peers than under a race-based policy.

The race-neutral simulations that include SES-based affirmative action either on its own or in combination with race recruiting also result in lines closer to the 45-degree line than the no affirmative action simulation, but not as close as the results from race-based affirmative action. High-achieving, Black and Hispanic students in these simulations are more academically matched to their peers than in simulations with no affirmative action. These lines both cross the 45-degree line at nearly the same location as the line from the no-affirmative-action simulation, suggesting that these policies sort similar numbers of students into institutions where their achievement falls below that of their peers

Race-recruiting policies on their own lead to the lowest proportion of students that are overmatched, the line crosses the 45-degree line at the lowest point of all simulations. However, it also produces the degree of undermatch for students with achievement below 1200 of all of the polices—the line is the farthest from the 45-degree line for this simulation.. Above this achievement, however, the line moves quickly towards the 45-degree line. In other words, race recruiting results in lower-achieving peers for lower achieving students, but higher achieving peers than under many policies for higher achieving students. Note that these results are due to changes in recruiting only at the top four schools but that changes at this margin have an effect throughout the distribution.

In sum, we see that affirmative action policies generally generate better match between own achievement and mean peer achievement than no affirmative action policy at all. In policies that are race-neutral, however, the improvement in match is not as large as that from our real-world race-based affirmative action baseline model.

Figure E1 is analogous to Figure 4, but for White students. Here we see that our simulated policies have very little impact on the average peer achievement of White students, particularly those with achievement less than about 1250. Above that level, race recruiting and no affirmative action policy result in similarly high achieving peers for White students, while the other three policy simulations result in peers that, on average, are about 15 points lower performing.

The results in Figures 4 and E1 are important if we are concerned with diversity-boosting polices as part of a broad higher education system. If, instead, we are concerned specifically with the students at institutions that use the policies, then we should focus on Figure 5 (and Appendix Figure E2), which presents these same comparisons as Figure 4 (and Appendix Figure E1), but only *for Black and Hispanic students enrolled in the top four schools* (i.e. within schools that use, or would use, affirmative action policies). Again, the 45-degree line indicates when a student's own achievement is equal to the average achievement of his or her peers. For Black and Hispanic students in these most selective schools, all of the policy simulations with the exception of the SES-based affirmative action and race recruitment combination perform roughly similarly: under each of them students with achievement below anywhere from 1340-1360 overmatch (Figure 5). This is the same value at which White students tend to be overmatched under the no policy simulation, however a greater proportion of Black and Hispanic students than White students score below that threshold (Figure E2). In contrast, Black and Hispanic students under the combination policy have peers with achievement levels about 50 points lower, on average, than the other policy simulations. Although it exposes Black and Hispanic students to academically weaker students, the combination policy results in the lowest rate of overmatch—Black and Hispanic students with achievement below 1300 overmatch, on average, in the combination simulation. This result appears to be driven mostly by the fourth ranked school, which receives a large influx of lower-achieving Black and Hispanic students in the combination scenario.

[Figure 5 here]

Latin Hypercube Sensitivity Analysis

To assess the extent to which the results presented above are sensitive to assumptions that we make in the model (specifically, the use of resource-effect values like achievement enhancement that we take from Reardon et al. (2016)), we conduct a Latin Hypercube analysis (Bruch & Atwood 2012; Segovia-Juarez et al. 2004). This analysis consists of generating 100 random combinations of parameter values (within plausible ranges) that govern resource-effect pathways, affirmative action, and recruitment policies, and then running our simulation once using each of these. This ensures that, in expectation, the parameters used during a model run are not correlated with each other. We next run regressions predicting college-level outcomes of interest (averaged over the last five years of each simulation for schools using affirmative action) using the parameters that we vary. The outcomes include mean academic achievement and resources of enrolled students, college rank, and proportion of enrolled students who are low resource or Black or Hispanic. These regression results are presented in Table 2, and show both affirmative action and recruitment policy effects independent of the assumptions that we make about resource effect pathways as well as the influence of resource effect pathway values. Overall, policy effects in this sensitivity analysis are consistent with what we present above, and our findings are fairly robust to the assumptions that we make about resource effect pathways magnitude. As expected, the biggest impact of varying resource effect magnitudes is on levels of low-resource student enrollment in the top 10 percent of colleges observed during simulations. The difference in this outcome between the highest and lowest parameter values that we explore never exceeds 10 percentage points. This can be seen in the “Resource-Apps Slope” row of Table 2, where doubling the “percent low resource” coefficient shows the estimated difference between simulations where every standard deviation increase in student resources is associated with an increase of 2 applications submitted and ones where student resources are not associated with the number of college applications submitted. For the sake of comparison, the “Race AA Magnitude” row leads to the calculation of an estimated 22 percentage point difference between low-income enrollment in simulations using “real world” racial affirmative action (i.e. 260 achievement points) strength and those without racial affirmative action.

[Table 2 here]

Discussion

The results of our simulations suggest at least three important patterns. First, within the range of values we investigate, and for colleges that approximate the ones that use affirmative action in admissions, neither SES-based affirmative action nor race-based recruiting policies on their own produce high levels of racial diversity relative to that achieved by race-based affirmative action. However, SES-based affirmative action in combination with targeted recruitment shows the potential to yield racial diversity levels comparable to race-based affirmative action. However, the associated cost of providing financial aid to these more financially needy students might render such policies infeasible in practice. Second, the use of affirmative action policies by some colleges reduces the diversity of similar-quality colleges that do not have such policies. Third, overall, the combination of SES-based affirmative action and race recruiting results in slightly fewer Black and Hispanic students that are academically overmatched than under race-based affirmative action, but the schools that use the combination policy also see an overall reduction in the academic achievement of the students they enroll.

The 2013 *Fisher I* decision requires universities to prefer “workable race-neutral alternatives” to race-based affirmative action. Suggesting one such alternative, Kahlenberg (1996) has argued that “class-based preferences provide a constitutional way to achieve greater racial and ethnic diversity” (p. 1064). However, our simulations suggest that unless SES-based affirmative action policies use a very strong preference for lower SES students, or are paired with effective race-based recruitment efforts, these policies result in racial diversity levels lower than those achieved under current race-based affirmative action policies. 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 racial diversity achieved under race-based affirmative action policies, and Long (2015) who found in Texas that that a number of race proxies could not reproduce the diversity achieved under race-based affirmative action.

Race-based affirmative action leads to racial diversity because it can select directly the students who will contribute most to racial diversity on a campus. SES-based affirmative action requires a strong relationship between SES and race in order to achieve racial diversity. Our analysis makes clear that the correlation currently observed in the real world means that even with unusually strong SES-based policies, institutions would only produce about half the diversity they would under race-based policies. This means that the operative question for institutions and policymakers pursuing racial diversity with an SES-based strategy is how much they are willing to weight SES in the admissions process given the limited racial diversity that it produces.

Special recruitment efforts that target URM students may help increase the effectiveness of potential SES-based admissions policies, however, there are several reasons to believe that even with this help it is unlikely these policies would be viable. First, the level of additional weight necessary for SES-based policies to produce levels of racial diversity up to even 80 percent of what to race-based policies produce would have to be exceptionally large, even with the help of race-targeted recruiting. Put in context, our empirically-based race-based affirmative action model gives Black students a weight of 260 achievement points over White students. In contrast, in our model using a strong SES-based approach, schools would need to give an additional weight of 150 points *for each standard deviation of SES*. This means that a student from two standard deviations below mean SES would have an admissions advantage 600 points higher than a student two standard deviations above mean SES, over two times larger than the weight we estimate is used in current race-based polices.

Second, because SES-based affirmative action increases SES diversity, colleges that consider such policies will have to consider what those policies will mean in terms of the additional students who need financial aid. Currently, very few colleges are able to meet the full demonstrated financial need of the students they enroll *without* the use of SES-based affirmative action, so an additional influx of lower-income students would likely stretch limited resources even more thinly. Moreover, our models assume that cost is not a barrier to enrollment for low-income, admitted students. In the absence of additional financial aid, many of the racial diverse beneficiaries of SES-based affirmative action in the real world may not choose to enroll at the rate they do in our model. That is, our estimates may overstate the effects of SES-based affirmative action policies unless such policies were coupled with increased financial aid. In contrast, race-based affirmative action alone yields higher proportions of URM students in the top colleges, although it produces relatively little additional socioeconomic diversity. In this respect, it is likely a less expensive and more direct means of increasing the racial diversity of colleges.

Third, the addition of targeted race-based recruitment and outreach offers a tempting solution to bans on race-conscious admissions policies, but this recruitment likely only adds to the cost of achieving racial diversity, assuming it is even possible. Race-targeted outreach without SES-based affirmative action appears to have helped the University of Washington recover from the loss of URM applicants after the state banned race-conscious affirmative action in admissions (Brown & Hirschman, 2006). However, the results of such efforts in California and Texas are less clear (Andrews, et al., 2016; Gándara, 2012; Geiser & Caspary 2005). In fact, despite *doubling* its recruitment budget, California still saw a substantial proportion of high-achieving URM students enroll in colleges outside the California system, even if they were admitted (Geiser & Caspary 2005).

Such findings call into question whether outreach and recruitment efforts can sway URM students enough to make a difference to campus diversity. Our models assumed that, at a maximum, colleges could raise their appeal to students by 100 points (comparable to the *average* SAT® score at a college appearing 100 points higher—or, roughly the difference between Tulane and Cornell). Further, our model was 100 percent efficient—all Black and Hispanic students felt the effect of our recruitment mechanism. It is hard to judge whether these assumptions carry much veracity in the real world. At the very least, the effort required to boost URM student recruitment efforts will only add to the cost of SES-based affirmative action programs. In other words, SES-based affirmative action plus race-targeted recruitment and outreach is a race-neutral alternative to race-conscious affirmative action, but it is not clear whether institutional budgets at public universities make it workable.

Affirmative action policies also affect all colleges, not just the colleges that use the policies. 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 diversity-boosting policies tend to reduce the diversity of campuses with no policies. Building on the work of Long and Tienda (2010) in Texas, 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 result 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 continue to 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.

Our models also 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.

Critics of race-based affirmative action have argued that it can lead to academic mismatch for URM students. We find that SES-based affirmative action, alone or in combination with race recruiting, lowers the average academic achievement of Black and Hispanic students' peers relative to no diversity-boosting policy or race-based affirmative action. This lowering of academic quality at colleges that use strong SES-based policies likely stems from the fact that colleges following these policies admit lower-achieving White students alongside Black and Hispanic students to achieve racial diversity. Our models do not presume that colleges would change their policies if their academic rank were falling. It is not clear that elite colleges in the real world would similarly want to lower their overall observable academic rank to the extent necessary to achieve racial diversity using race neutral policies, again suggesting that such policies may not be viable.

The models presented in this paper do not directly address issues of cost or financial aid. We do, however, indirectly include elements of race-targeted financial aid in our recruitment parameters: Financial aid and other forms of tuition discounting are implied in efforts that would make a college more desirable to targeted students. It is likely that the direct inclusion of cost and financial aid considerations would mute some of the effects of affirmative action policies unless the policies are accompanied by increased financial aid or other greatly modified tuition structures. URM and low-income students would presumably be discouraged from applying to expensive, selective colleges, limiting the ability of affirmative action policies of any type to be effective. Our results, therefore, may represent an upper bound on the potential effectiveness of various affirmative action polies. The complexities of this issue are worth exploring in future research and are an area to which policy makers should pay close attention.

Conclusion

In *Fisher I*, the Supreme Court challenged states and universities to find workable race-neutral strategies that can achieve educationally-beneficial diversity and *Fisher II* pressed them to continue to evaluate the ongoing need for any race-conscious policies they use. Racial diversity is, the court has agreed, educationally beneficial (*Grutter v. Bollinger*, 2003). The question, then, is how best to achieve such diversity in constitutionally permissible ways. Perhaps the best way would be to eliminate racial gaps in high school achievement and graduation rates. Doing so would certainly go a long way toward equalizing access to selective colleges and universities without the need for race-based affirmative action. Although these gaps have narrowed moderately in the last two decades (Reardon, Robinson-Cimpian, & Weathers, 2015; Murnane, 2013), they are still very large, without a clear indication that they will be eliminated any time soon.

Until racial disparities in educational preparation are eliminated, colleges need other strategies to achieve diversity goals. Our analysis here suggests that affirmative action policies based on SES are unlikely to reproduce high levels of racial diversity relative to those achieved by race-based policies unless they are paired with targeted race recruiting and provide admissions boosts that may prove prohibitively large and costly. That is not to say that SES-based 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.

References

Andrews, R. J., Imberman, S. A., & Lovenheim, M. F. (2016). Recruiting and Supporting Low-Income, High-Achieving Students at Flagship Universities (Working Paper No. 22260). Cambridge, MA: National Bureau of Economic Research.

Arcidiacono, P., Aucejo, E., Coate, P., & Hotz, V. J. (2014). Affirmative action and university fit: Evidence from Proposition 209. IZA Journal of Labor Economics, 3, 7.

Arcidiacono, P., Khan, S., & Vigdor, J. L. (2011). Representation versus assimilation: How do preferences in college admissions affect social interactions? Journal of Public Economics, 95, 1–15.

Arcidiacono, P., & Lovenheim, M. (2014). Affirmative action and the quality-fit tradeoff (Working Paper No. 20962). Cambridge, MA: National Bureau of Economic Research.

Backes, B. (2012). Do affirmative action bans lower minority college enrollment and attainment? Evidence from statewide bans. Journal of Human Resources, 47, 435-455.

Bastedo, M. N., & Jaquette, O. (2011). Running in place: Low-income students and the dynamics of higher education stratification. Educational Evaluation and Policy Analysis, 33, 318-339.

Becker, B. J. (1990). Coaching for the Scholastic Aptitude Test: Further synthesis and appraisal. Review of Educational Research, 60, 373-417.

Bowen, W. G., & Bok, D. (1998). The Shape of the River: Long-term Consequences of Considering Race in College and University Admissions. Princeton, NJ: Princeton University Press.

Bowen, W. G., Kurzweil, M. A., & Tobin, E. M (2005). Equity and Excellence in American Higher Education. Charlottesville, VA: University of Virginia Press.

Brown, S. K., & Hirschman, C. (2006). The end of affirmative action in Washington State and its impact on the transition from high school to college. Sociology of Education, 79, 106-130.

Buchmann, C., Condron, D. J., & Roscigno, V. J. (2010). Shadow education, American style: Test preparation, the SAT® and college enrollment. Social Forces, 89, 435-461.

Bruch, E., & Atwood, J. (2012). Agent-based models in empirical social research. Working paper.

Carnevale, A. P., & Rose, S. J. (2004). Socioeconomic status, race/ethnicity, and selective college admissions. In R. D. Kahlenberg (Ed.), America's Untapped Resource: Low-Income Students in Higher Education (pp. 101–156). New York: Century Foundation Press.

Carnevale, A. P., & Strohl, J. (2010). How increasing college access is increasing inequality, and what to do about it. In R.D. Kahlenberg (Ed.) Rewarding Strivers: Helping Low-Income Students Succeed in College (pp. 71-190). New York: Century Foundation Press.

Carnevale, A. P., Rose, S. J., & Strohl, J. (2014). Achieving racial and economic diversity with race-blind admissions policy. In R. D. Kahlenberg (Ed.), The future of affirmative action: New paths to higher education diversity after Fisher v. University of Texas (pp. 187–202). New York: Century Foundation Press.

Dickson, L. M. (2006). Does ending affirmative action in college admissions lower the percent of minority students applying to college?. Economics of Education Review, 25, 109-119.

Dillon, E. W., & Smith, J. A. (2015). The consequences of academic match between students and colleges (IZA Discussion Paper No. 9080).

Epstein, J. M. (1999). Agent-based computational models and generative social science. Complexity, 4, 41-60.

Espenshade, T. J., & Radford, A. W. (2009). No Longer Separate, Not Yet Equal: Race and Class in Elite Admission and College Life. Princeton, NJ: Princeton University Press.

Fisher v. University of Texas at Austin, 570 U.S. ________ (2013).

Fisher v. University of Texas at Austin, 579 U.S. ________ (2016).

Fu, C. (2014). Equilibrium tuition, applications, admissions and enrollment in the college market. Journal of Political Economy, 122, 225-281.

Gaertner, M. N., & Hart, M. (2013). Considering class: College access and diversity. Harvard Law and

Policy Review, 7, 367–403.

Gandara, P. (2012). California: A case study in the loss of affirmative action. Los Angeles: The Civil Rights Project.

Gratz v. Bollinger, 539 U.S. 244 (2003).

Grutter v. Bollinger, 539 U.S. 306 (2003).

Gurantz, O., Hurwitz, M., & Smith, J. (2017). College Enrollment and Completion Among Nationally Recognized High-Achieving Hispanic Students. Journal of Policy Analysis and Management, 36, 126-153.

Hinrichs, P. (2012). The effects of affirmative action bans on college enrollment, educational attainment, and the demographic composition of universities. Review of Economics and Statistics, 94, 712-722.

Horn, C. L. & Flores, S. M. (2003). Percent plans in college admissions: A comparative analysis of three states' experiences. Cambridge, MA: The Civil Rights Project at Harvard University.

Howell, J. S. (2010). Assessing the impact of eliminating affirmative action in higher education. Journal of Labor Economics, 28, 113–166.

Hoxby, C. M., & Avery, C. (2012). The missing "one-offs": The hidden supply of high-achieving, low income students (Working Paper No. 18586). Cambridge, MA: National Bureau of Economic Research.

Institute of Education Sciences (2012). NCES Common Core of Data. U.S. Department of Education, National Center for Education Statistics. Washington, DC.

Kahlenberg, R. D. (1996). Class-based affirmative action. California Law Review, 84, 1037–1099.

Kahlenberg, R. D. (2012). The future of school integration: Socioeconomic diversity as an education reform strategy. New York, NY: Century Foundation Press.

Kane, T. J. (1998). Racial and ethnic preferences in college admissions. In C. Jenks & M. Phillips (Eds.), The Black-White test score gap. Washington, DC: Brookings Institution Press.

Lim, M. (2013). Percent plans: A workable, race-neutral alternative to affirmative action. Journal of

College and University Law, 39, 127-163.

Long, M. C. (2004). Race and college admission: An alternative to affirmative action? The Review of Economics and Statistics, 86, 1020–1033.

Long, M. C. (2007). Affirmative action and its alternatives in public universities: What do we know? Public Administration Review, 67, 311–325.

Long, M. C. (2015). Is there a "workable" race-neutral alternative to affirmative action in college admissions?. Journal of Policy Analysis and Management, 34, 162-183.

Murnane, R. (2013). U.S. high school graduation rates: Patterns and explanations. Journal of Economic Literature, 51, 370–422.

Niu, S. X., & Tienda, M. (2010). The impact of the Texas top 10 percent law on college enrollment: A regression discontinuity approach. Journal of Policy Analysis and Management, 29, 84-110.

Powers, D. E., & Rock, D. A. (1999). Effects of coaching on SAT® I: Reasoning test scores. Journal of Educational Measurement, 36, 93-118.

Reardon, S. F., Baker, R., & Klasik, D. (2012). Race, income, and enrollment patterns in highly selective colleges, 1982-2004. Stanford Center on Poverty and Inequality, Stanford University. Retrieved from http://cepa.stanford.edu/content/race-income-and-enrollmentpatterns-highly-selective-colleges-1982-2004.

Reardon, S. F., Kasman, M., Klasik, D., & Baker, R. B. (2016). Student resources and stratification among colleges: An agent-based simulation of five mechanisms of the college sorting process. Journal of Artificial Societies and Social Simulation, 19, 1, 8.

Reardon, S. F., & Rhodes, L. (2011). The effects of socioeconomic school integration policies on racial school segregation. In E. Frankenberg & E. DeBray (Eds.), Integrating schools in a changing society. Chapel Hill: University of North Carolina Press.

Reardon, S., Robinson-Cimpian, J., & Weathers, E. (2015). Patterns and trends in racial/ethnic and socioeconomic academic achievement gaps. In H. Ladd & M. Goertz (Eds.), Handbook of Research in Education Finance and Policy. New York, NY: Routledge.

Reardon, S. F., Yun, J. T., & Kurlaender, M. (2006). Implications of income-based school assignment policies for racial school segregation. Educational Evaluation and Policy Analysis, 28, 49–75.

Sander, R. H. (1997). Experimenting with class-based affirmative action. Journal of Legal Education, 47, 472–503.

Sander, R. H. (2004). A systemic analysis of affirmative action in American law schools. Stanford Law Review, 57, 367–483.

Segovia-Juarez, J. L., Ganguli, S., & Kirschner, D. (2004). Identifying control mechanisms of granuloma formation during *M. tuberculosis* infection using an agent-based model. Journal of Theoretical Biology, 231 357–376.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty, 5, 297-323.

Xiang, A., & Rubin, D. B. (2015). Assessing the potential impact of a nationwide class-based affirmative action system. Statistical Science, 30, 297-327.

Table 1. Agent-Based Simulation Model (ABM) Parameters

Parameter	Value	Source
Number of students	10,000	n/a
percent White	60 percent	NCES Common Core of Data, 2012
percent Black	15 percent	NCES Common Core of Data, 2012
percent Hispanic	20 percent	NCES Common Core of Data, 2012
percent Asian	5 percent	NCES Common Core of Data, 2012
Number of colleges	40	n/a
College capacity	150 students/college	n/a
<u>Student academic achievement</u>		ELS
White	*achievement ~N(1052, 186)*	
Black	*achievement ~N(869, 169)*	
Hispanic	*achievement ~N(895, 185)*	
Asian	*achievement ~N(1038, 202)*	
<u>Student resources</u>		ELS
White	*resources*~*N*(.198, .657)	
Black	*resources*~*N*(-.224, .666)	
Hispanic	*resources*~*N*(-.447, .691)	
Asian	*resources*~*N*(.012, .833)	
<u>Resources-achievement correlations</u>		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., 2016
Own achievement reliability (how well students see their own achievement)	0.7 + a*(*resources*); a=0.1	Reardon et al., 2016
Achievement reliability (how well colleges see student achievement)	0.8	Reardon et al., 2016
Apparent achievement (perceived achievement, increased or decreased through achievement enhancement)	*perceived achievement* + b*(*resources*)*(race-specific achievement standard deviation); b=0.1	Becker, 1990; Buchmann, Condron, & Roscigno, 2010; Powers & Rock, 1999; Reardon et al., 2016
Number of applications	4 + INT[c*(*resources*)]; c=0.5	ELS
Utility of college attendance	d + e*(*perceived quality*); d=-250, e=1	Reardon et al., 2016

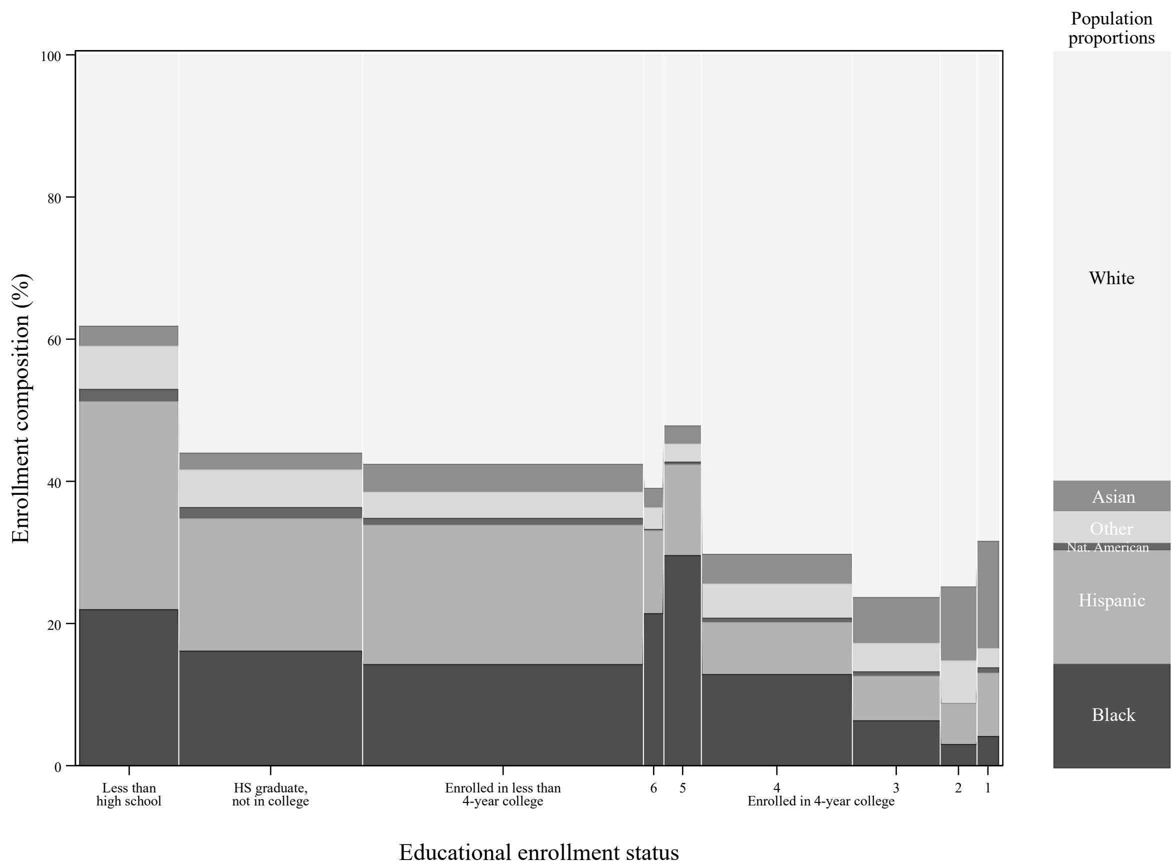
Note. Quality and achievement reliability bound by minimum values of 0.5 and maximum values of 0.9. ELS = Educational Longitudinal Study.

Table 2. Latin Hypercube Analysis

Independent Variable	Model/Dependent Variable: College Quality	Mean College Resources	College Quality Rank	Percent Low Resource	Percent Black/ Hispanic	Independent Variable Ranges: Mean	Min	Max
	b/(se)	b/(se)	b/(se)	b/(se)	b/(se)	Mean	Min	Max
Information Reliability	91.572***	0.397***	4.111	-16.052***	-15.641	.1	0	.2
	(16.600)	(0.077)	(2.641)	(4.181)	(8.651)			
Resource-Apps Slope	5.269**	0.078***	0.493	-4.779***	-3.386***	1	0	2
	(1.599)	(0.007)	(0.254)	(0.403)	(0.833)			
Utility Slope	2.165	0.011	0.284	-0.688	-1.487	1	0	2
	(1.622)	(0.008)	(0.258)	(0.409)	(0.846)			
Resource-App Enhancement	36.411*	0.961***	2.358	-47.376***	-2.072	.1	0	.2
	(16.003)	(0.074)	(2.546)	(4.030)	(8.340)			
SES AA Magnitude	-0.372***	-0.004***	-0.043***	0.186***	0.174***	75	0	150
	(0.022)	(0.000)	(0.003)	(0.005)	(0.011)			
Race AA Magnitude	-0.366***	-0.002***	-0.041***	0.086***	0.234***	150	0	300
	(0.011)	(0.000)	(0.002)	(0.003)	(0.006)			
Race Recruit Magnitude	-0.154***	-0.001***	-0.019***	0.047***	0.122***	100	0	200
	(0.016)	(0.000)	(0.003)	(0.004)	(0.008)			
Constant	1375.603***	0.767***	102.009***	5.886***	-9.407***			
	(4.753)	(0.022)	(0.756)	(1.197)	(2.477)			
N	100	100	100	100	100			
R-Sqr	0.941	0.970	0.885	0.961	0.957			

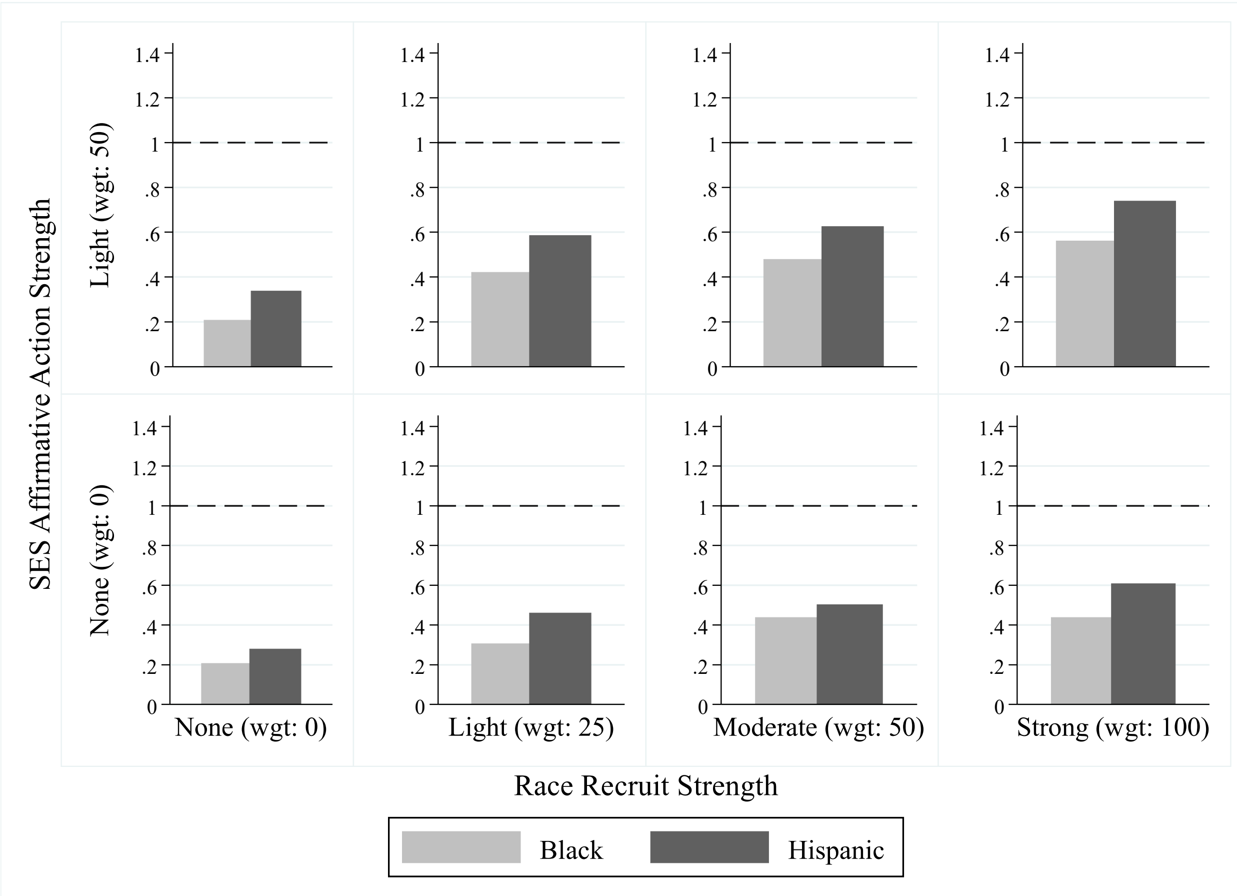
Note. “Percent Low Resource” is defined as the percentage of students from the bottom two quintiles of the resources distribution. Coefficients give the change in the given outcome associated with varying the given parameter between the extremes listed to the right of the table.

Figure 1. The racial composition of postsecondary destinations for the high school class of 2004.



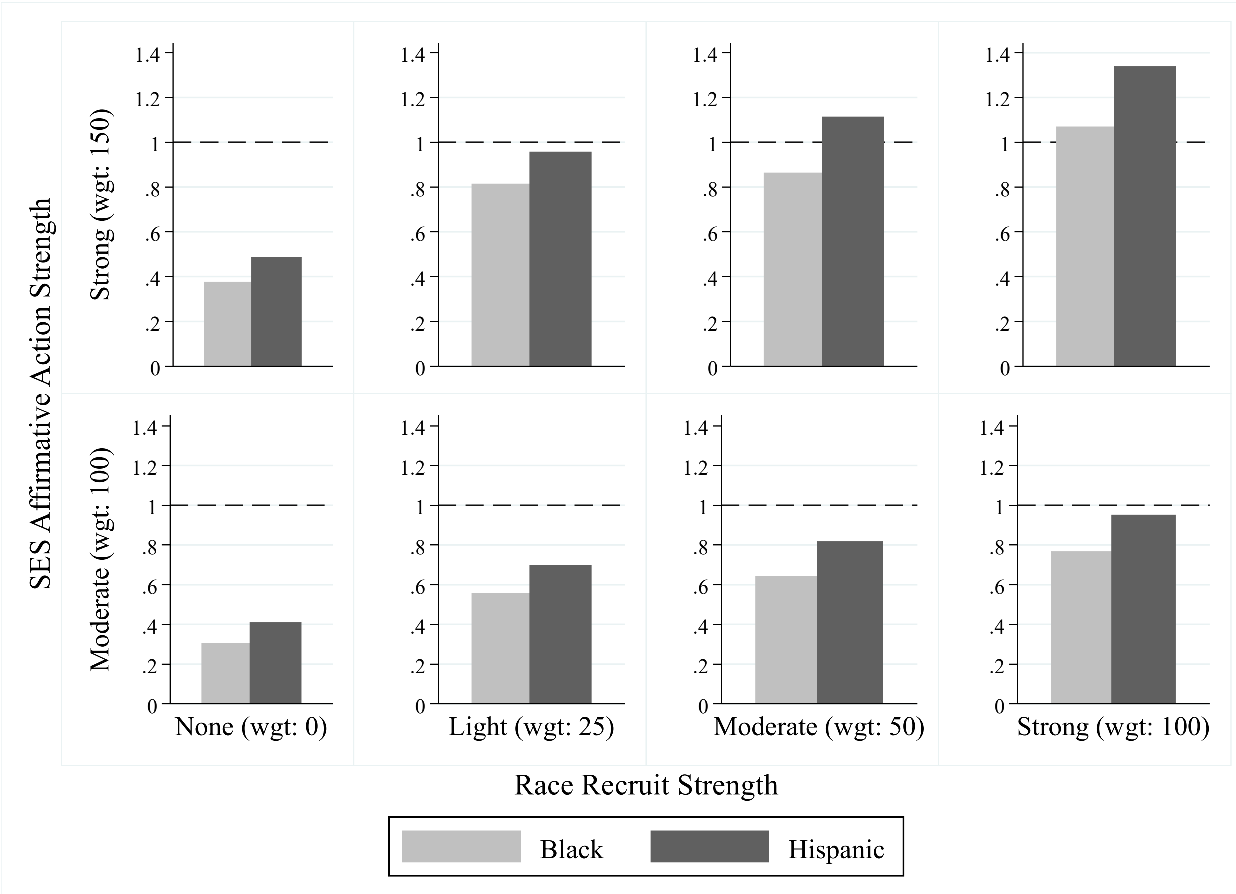
Notes. Reproduced from Reardon, Baker, & Klasik (2012). Figure shows the postsecondary enrollment status of members of the high school class of 2004 by race and type of college or university. In particular, we break college enrollment into enrollment in a less-than-four-year college and, if a student is enrolled in a four-year college, we divide schools according to the Barron's selectivity rating of the school (from the least selective [6] to most selective [1]). 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. Source: Educational Longitudinal Study, 2002.

Figure 2. Black and Hispanic Enrollment in Colleges using SES-Based Affirmative Action and Race-Based Recruitment, as a share of estimated Black and Hispanic enrollment under race-based affirmative action (using estimated real-world affirmative action weight)



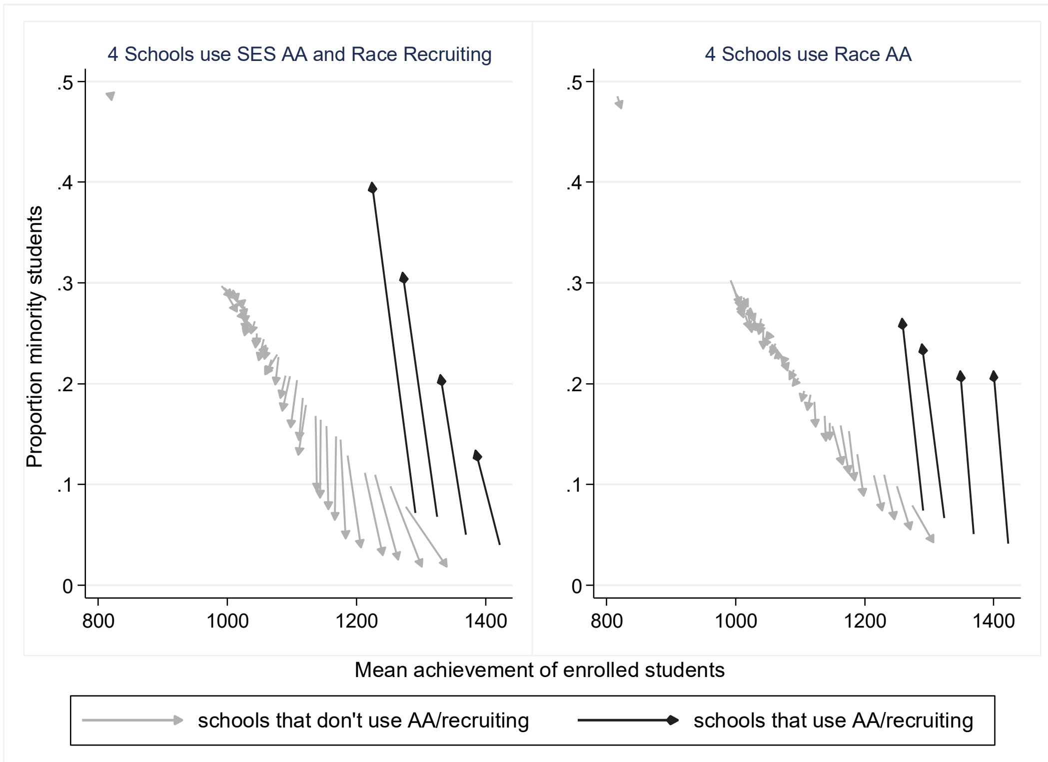
Notes. Black and Hispanic enrollment in the four highest-ranked colleges shown as a percentage of the Black and Hispanic enrollment achieved under the estimated real-world, race-based affirmative action weight of 260 (indicated with the dotted line). Source: authors' simulation.

Figure 2 (continued). Black and Hispanic Enrollment in Colleges using SES-Based Affirmative Action and Race-Based Recruitment, as a share of estimated Black and Hispanic enrollment under race-based affirmative action (using estimated real-world affirmative action weight)



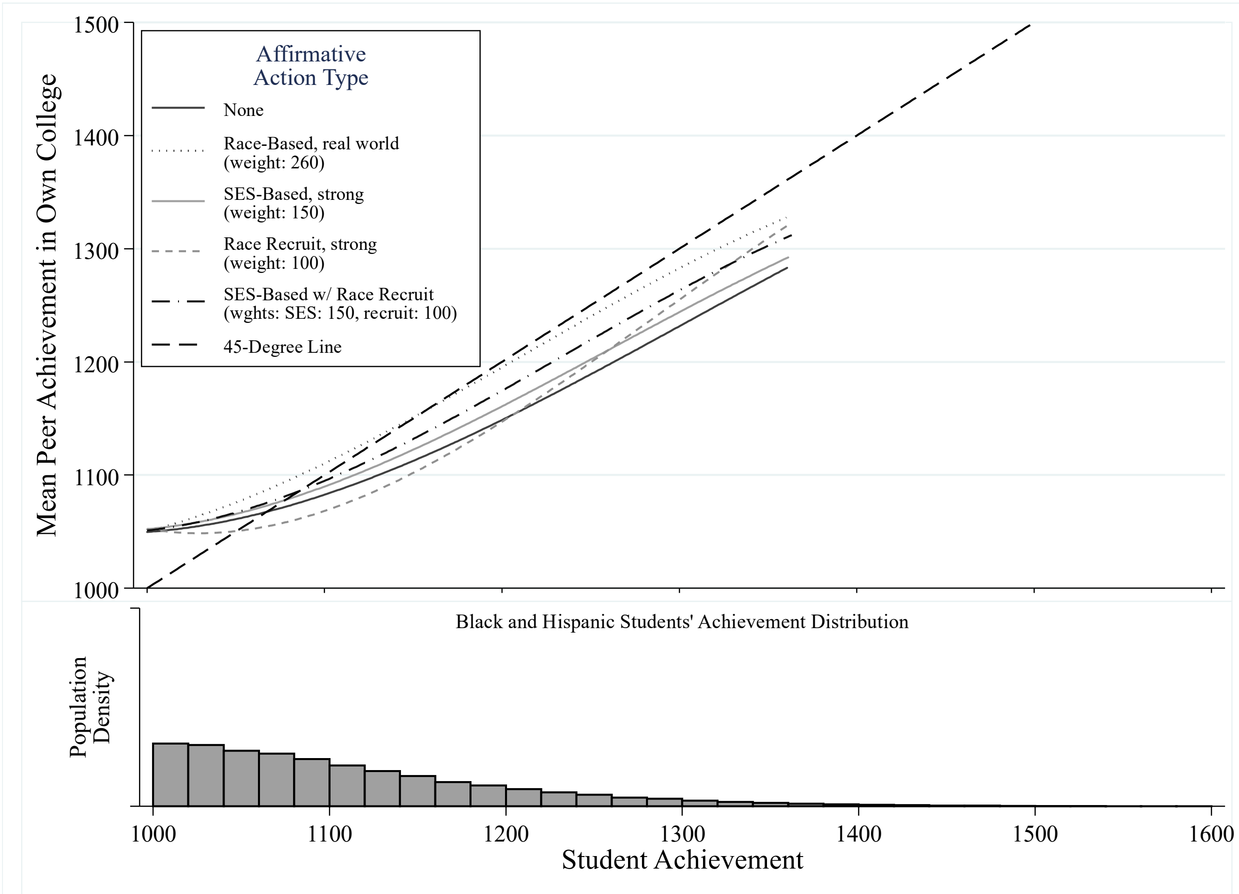
Notes. Black and Hispanic enrollment in the four highest-ranked colleges shown as a percentage of the Black and Hispanic enrollment achieved under the estimated real-world, race-based affirmative action weight of 260 (indicated with the dotted line). Source: authors' simulation.

Figure 3. Mean achievement and proportion minority by type of admission policies used by top four schools.



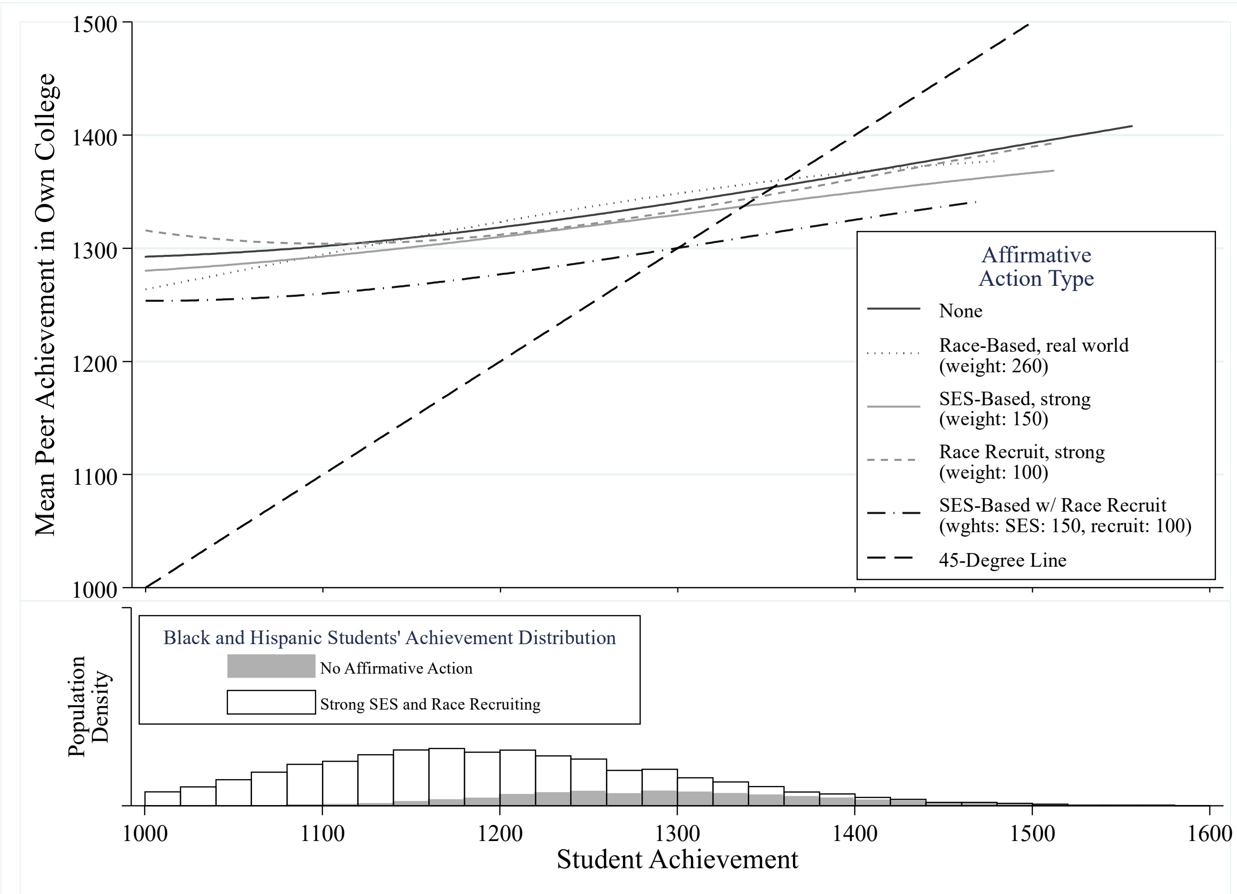
Notes. The left panel gives the results of the scenario where strong socioeconomic-based affirmative action and race-recruiting policies are used by the top four schools. The right panel gives the results of the scenario where the top four schools use strong race-based affirmative action policies. Arrows start at a school's position in year 15 when it was not using affirmative action, and end at the school's position in year 30. The left-most arrow captures students who do not enroll in college in our simulation. Source: authors' simulation.

Figure 4. Mean achievement of Black and Hispanic students' college classmates, by own achievement, and affirmative action type; results from all schools; top four ranked schools use affirmative action.



Source: authors' simulation.

Figure 5. Mean achievement of Black and Hispanic students' college classmates, by own achievement, and affirmative action type; results from top four ranked schools; top four ranked schools use affirmative action.



Source: authors' simulation.

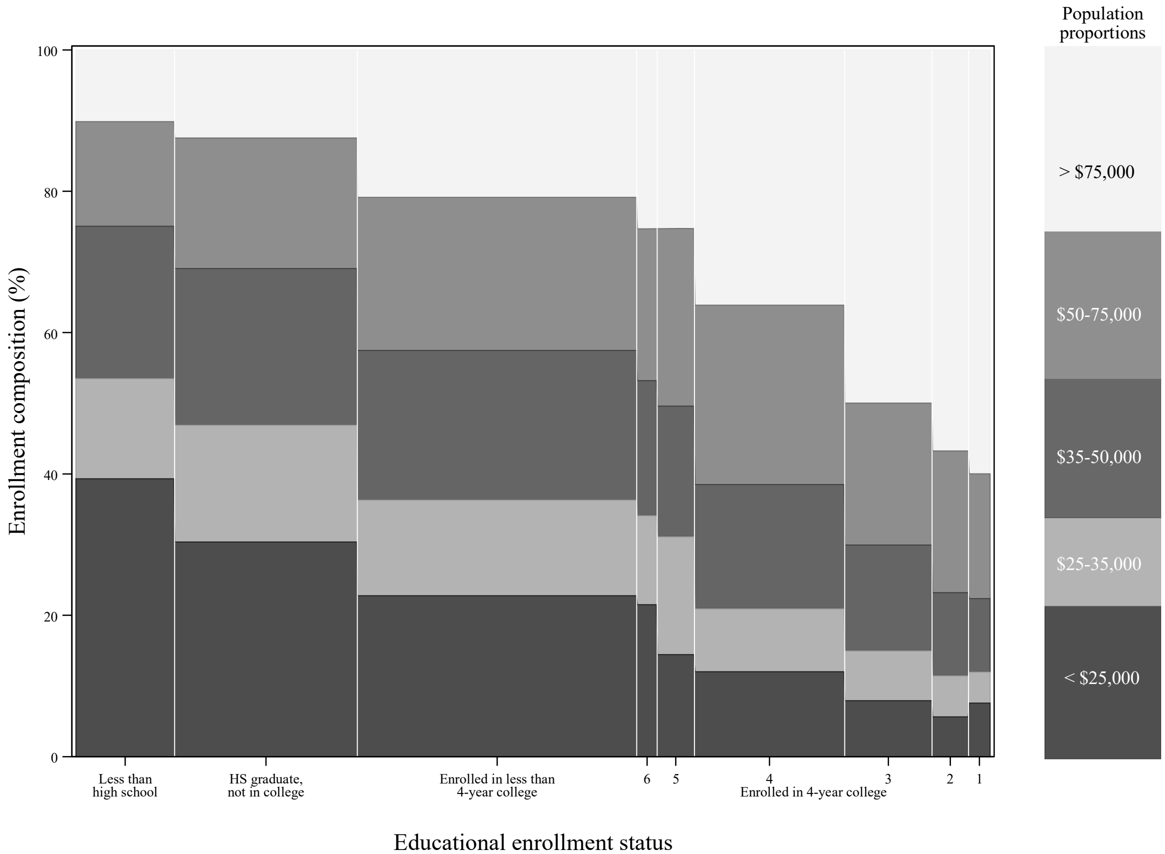
Appendix A. Socioeconomic and racial composition of real-world and simulated colleges

In Appendix A we provide figures representing the student composition of real-world post-secondary destinations (Figure A1) and simulated colleges under a range of admissions policies (Figures A2-A5). In the results presented in the main text we focus on testing the effects of SES-based affirmative action and race-based recruiting strategies, as compared to race-based affirmative action policies, on the student composition (in terms of both race and achievement). Our goal is to provide an extended view of the effects of our simulated admissions policies and again compare them to the effects of race-based affirmative action.

In Figure A2 we extend Figure 2 by showing the full racial composition of schools using various combinations of SES-based affirmative action and race-based recruiting. We again see the important complementary effects of these policies, and the small effect that SES-based affirmative action can have on racial diversity if it is not combined with race recruiting. In Figure A3 we show the effects of these same policies on the SES composition of schools. Unsurprisingly, race recruiting has little effect on the SES composition of schools, and SES-based affirmative action has a large effect.

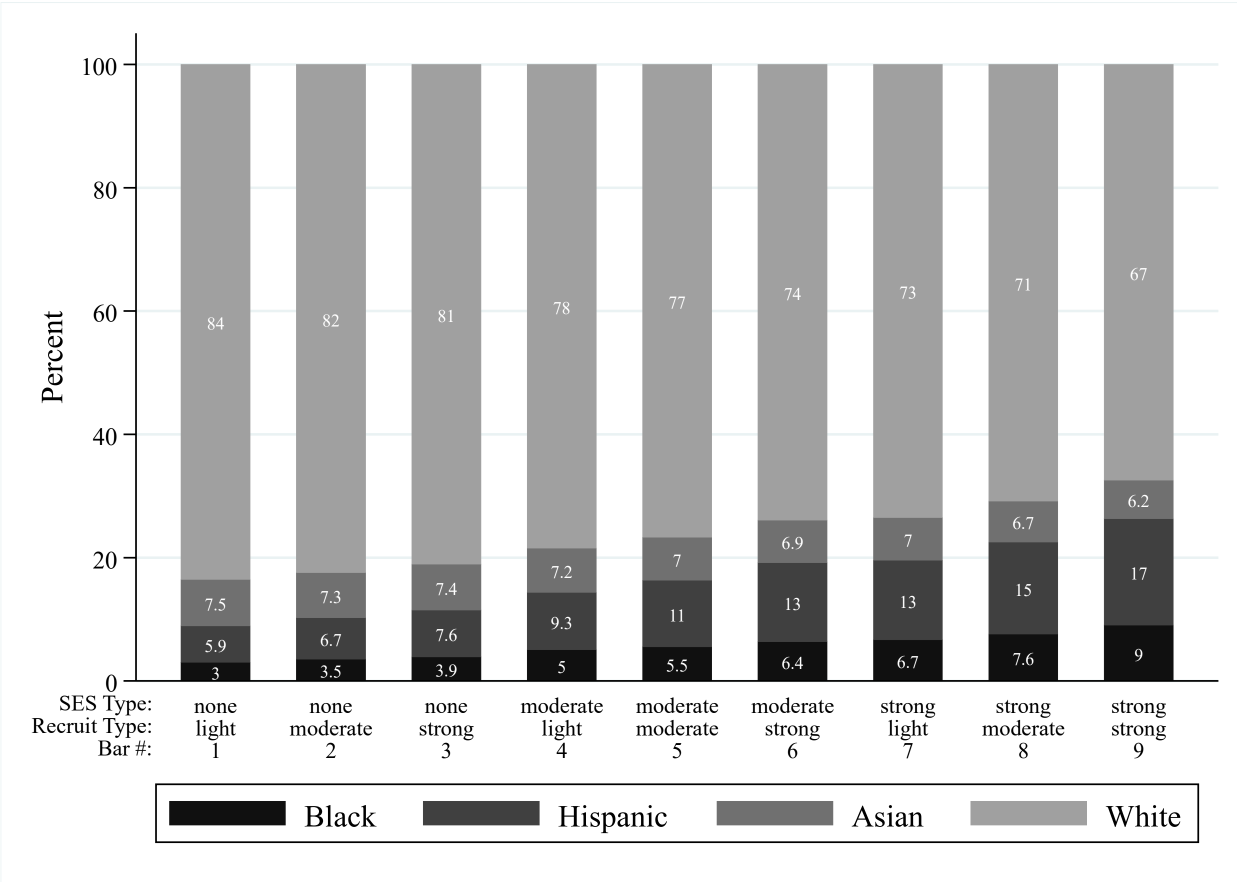
In Figures A4 and A5 we provide the racial and SES compositions of schools using various combinations of race- and SES-based affirmative action policies. These figures provide an extension to Figure 2 and demonstrate the effects of using SES- and race-based affirmative action policies alone and in combination. Both in terms of racial composition and SES- composition, the affirmative action policies have interactive effects: schools are more diverse when the policies are used in tandem. But, each policy has a much greater effect on its focal group than it does on the other (e.g. SES-based affirmative has a much smaller effect on the racial diversity of a school than the SES diversity of a school). SES-based affirmative action has little effect on the racial diversity of schools unless it is used with a race-targeted policy.

Figure A1: Income Composition of Postsecondary Destinations, Class of 2004



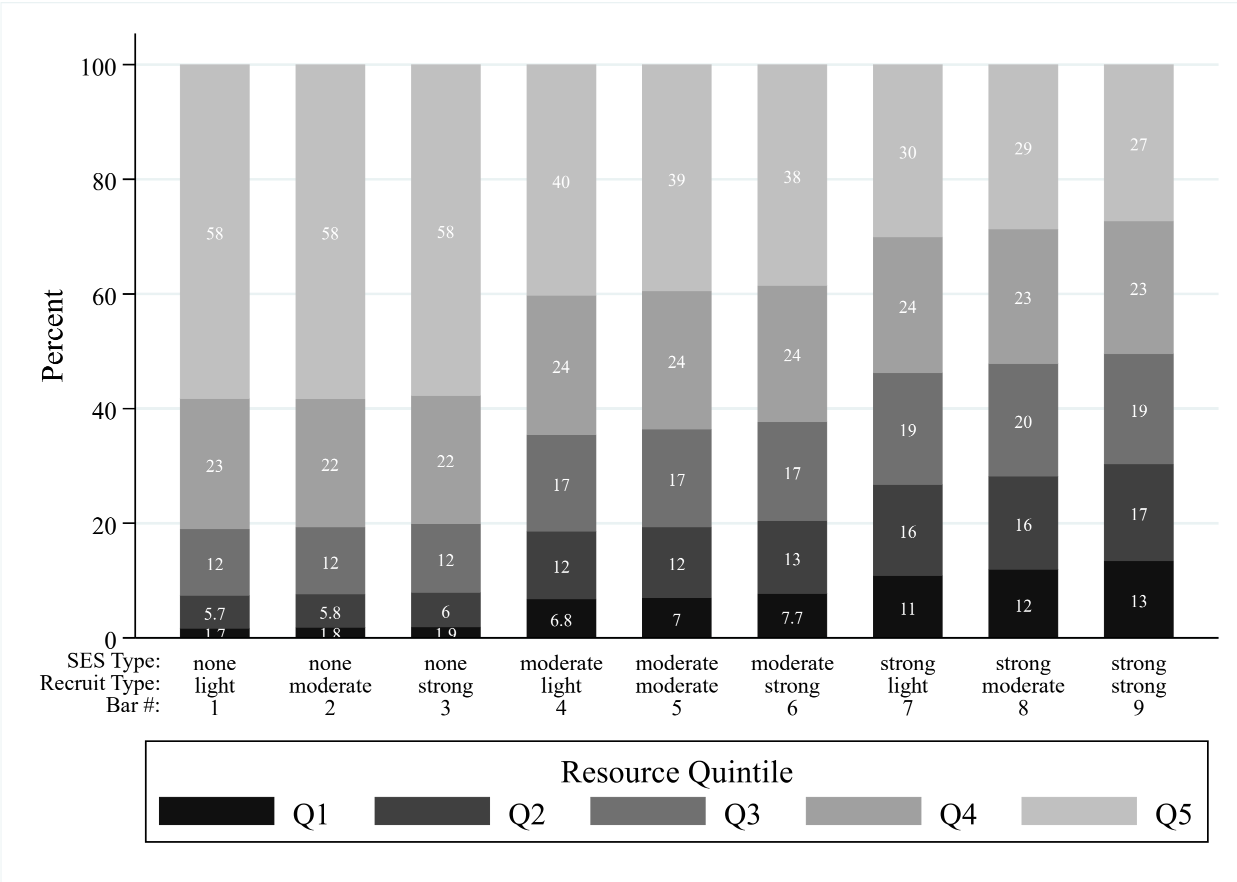
Notes: Figure A1 shows the postsecondary enrollment status of members of the high school class of 2004 by family income and type of college or university. The width of each bar represents the percentage of the college-age population enrolled in different types of colleges and universities (or not enrolled in any college, in the case of the leftmost bars). The vertical dimension describes the income composition of students enrolled in each type of postsecondary institution. Source: Educational Longitudinal Study, 2002.

Figure A2. The racial composition of colleges using SES-based affirmative action and race-based recruitment, by affirmative action and recruitment strength.



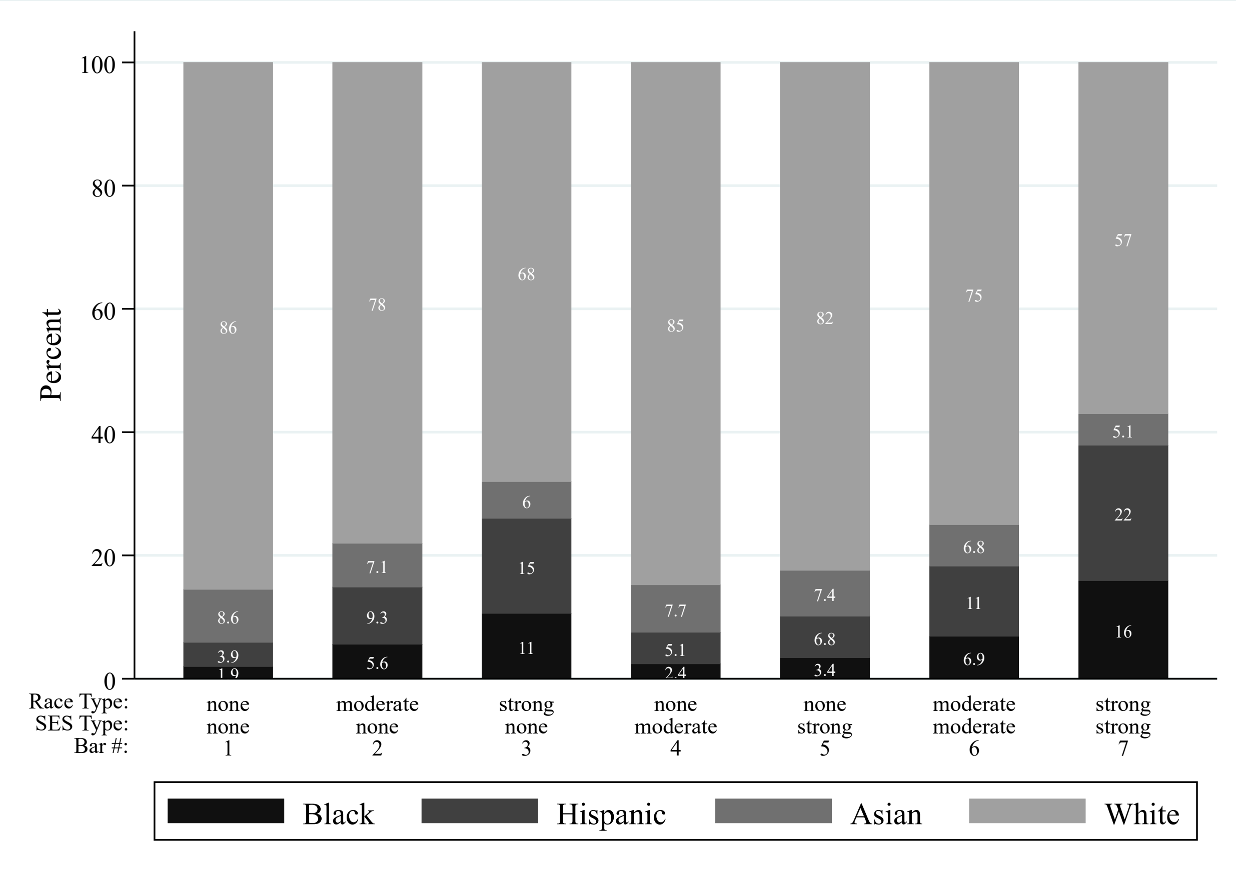
Notes. Simulated population proportions are: 60 percent White, 20 percent Hispanic, 15 percent Black, and 5 percent Asian. Moderate and strong SES-based affirmative action scenarios utilize a weight equivalent to 75 and 150 achievement points per standard deviation of resources. Recruitment weights are: light, 25 points; moderate, 50 points; strong, 100 points. SES is socioeconomic status. Source: authors' simulation.

Figure A3: The socioeconomic composition of colleges using SES-based affirmative action and race-based recruitment, by affirmative action and recruitment strength.



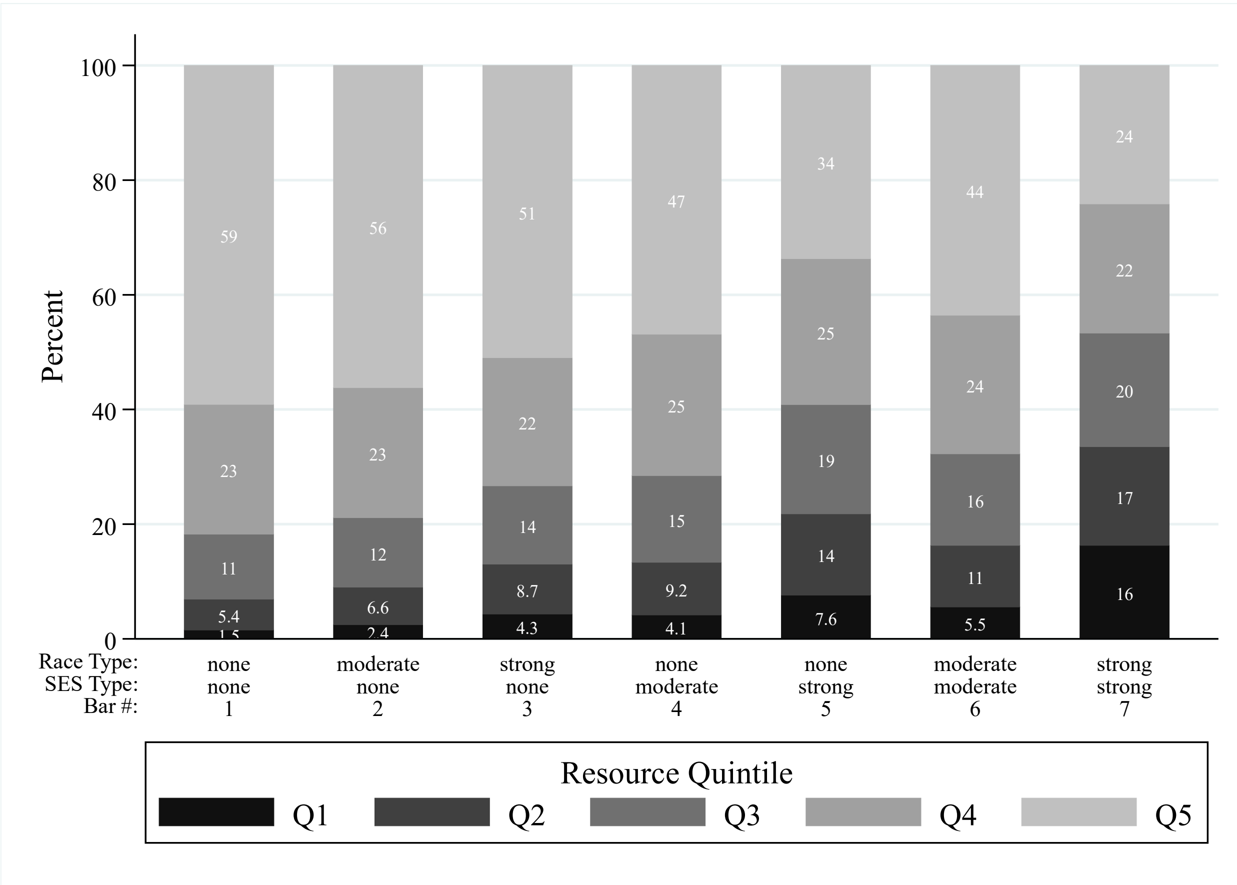
Notes. Moderate and strong SES-based affirmative action scenarios utilize a .375 and .75 weight, respectively, equivalent to 75 and 150 achievement points. Recruitment weights are: light, 25 points; moderate, 50 points; strong, 100 points. SES is socioeconomic status. Source: authors' simulation.

Figure A4. The racial composition of colleges using affirmative action, by affirmative action type.



Notes. Simulated population proportions are: 60 percent White, 20 percent Hispanic, 15 percent Black, and 5 percent Asian. Moderate and strong race-based affirmative action scenarios utilize a weight equivalent to 150 and 300 achievement points. Moderate and strong SES-based affirmative action scenarios utilize a weight equivalent to 75 and 150 achievement points per standard deviation of resources. Bar 3 is most analogous to using the estimated real world affirmative action race weight of 260 achievement points. SES is socioeconomic status. Source: authors' simulation.

Figure A5. The socioeconomic composition of colleges using affirmative action, by affirmative action type.



Notes. Moderate and strong race-based affirmative action scenarios utilize a weight equivalent to 150 and 300 achievement points. Moderate and strong SES-based affirmative action scenarios utilize a weight equivalent to 75 and 150 achievement points per standard deviation of resources. Bar 3 is most analogous to using the estimated real world affirmative action race weight of 260 achievement points. SES is socioeconomic status. Source: authors' simulation.

Appendix B. Estimates of the relative admissions weight given to race, socioeconomic status (ses), and academic performance

In this appendix we examine past efforts to estimate the relative weights given to race, SES, and academic performance in selective college admissions processes and provide more details on our own analyses. 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.[10] 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. 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).

[10] This may seem counterintuitive, but it results from the fact that racial differences in mean test scores mean that there are more URM 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 URM students because of the higher proportion of White students with very high scores.

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 percent 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, 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 models 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.[11] 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 percent 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

[11] 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.

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

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: 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.

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

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: 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 SES 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.

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., 2016).

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.

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

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

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

where ρ^Q_s, 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:

$$U_{cs}^{*} = a_s + b_s(Q_{cs}^{*}),$$

(C.3)

where a_s is the intercept of a linear utility function and b_s is the slope. Reardon et al. (2016) 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, as described in Table 1.

When present in a given simulation run, race-based recruitment policies (like affirmative action policies) are activated in the appropriate colleges after year 15 of model runs, allowing college quality and enrollment behavior (i.e. colleges' enrollment yields) to stabilize first. At this point, colleges' binary recruitment statuses (S_c)—which had previously all been 0—are set based on model parameters that determine which schools will use recruitment (e.g. the top 4 colleges) and remain constant through the remainder of the model run. Utility is then calculated using model-specific recruitment magnitude values (*L*):

$$U_{cs}^{*} = a_s + b_s(Q_{cs}^{*}) + R_{sc}.$$

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

$$A_s^{*} = A_s + \alpha_s + e_s;\ e_s \sim N(0, \sigma_s),$$

(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:

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

(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.[12]

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

$$P_{cs} = f(A_s^* - Q_{cs}^*),$$

(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

[12] 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., 2016). 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., 2016). 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.

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: $U_{C_1s}^* \geq U_{C_2s}^* \geq \cdots \geq U_{C_ns}^*$. 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

$$E_s^*\{C_1, C_2, \dots, C_{n_s}\} = P_{C_1s}^* \cdot U_{C_1s}^* + \left(1 - P_{C_1s}^*\right) \cdot E_s^*\{C_2, \dots, C_{n_s}\}. \tag{C.7}$$

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. (2016) 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):

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

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.[13]

When present in a given simulation run, affirmative action policies (like recruitment policies) are activated in the appropriate colleges after year 15 of model runs, allowing college quality and enrollment behavior (i.e. colleges' enrollment yields) to stabilize first. At this point, colleges' binary affirmative action statuses (T_c) —which had previously all been 0—are set based on model parameters that determine which schools will use affirmative action (e.g. the top 4 colleges) and remain constant 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:

$$A_{cs}^{***} = A_{cs}^{**} + T_c[G \cdot (Black_s | Hispanic_s) + H \cdot R_s].$$

[13] 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., 2016). 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.

(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:

$$Yield_c = 0.2 + 0.6(College\ quality\ percentile),$$

(C.11)

with the lowest-quality college expecting slightly over 20 percent of admitted students to enroll and the highest quality college expecting 80 percent 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:

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

(C.12)

where $\bar{A}_c$ is the average value of A_s among the newest cohort of students enrolled in college c.

Simulation Duration

We run the model for 30 years. In our simulations, this is a sufficient length of time for key dynamics within the model to reach relatively stable states under most conditions (see Figure C1 through C3), but under conditions with very strong policy magnitudes these dynamics will not stabilize within this timeframe (see Figure C4) given the model dynamics described above. Note, however, that the model will always stabilize within this timeframe (and, in fact, much sooner) if we turn off college quality updating when policies become active in year 15 of simulations runs (see Figure C6).

We argue that model dynamics that we describe and the runtime that we select allow for a consistent and realistic comparison between policy scenarios. Both selecting a longer runtime and freezing college quality in order to ensure stability in every simulation make arguably unrealistic assumptions about model behavior. For example, in simulations that allow college quality to update (this is all simulations in the paper, save that of figure C6), one assumption of the simulation is that colleges will not alter, or even cease, affirmative action strategies in the face of potentially dramatic decreases in quality rank or selectivity. As figure C5 makes clear, the top four ranked colleges, which begin using affirmative action in year 15, all experience a gradual decline in their quality ranking over time, as they continue to implement very aggressive affirmative action and recruitment strategies. It is unlikely that top colleges in the real world would so willingly sacrifice their quality ranking.

Fixing college quality, however, is an equally problematic assumption. Here the assumption is that a college using affirmative action will see absolutely no change in reputation over time, even in the face of changing student achievement, race, and SES composition.

Because we do not have sufficient guidance from literature or data to characterize the “stickiness” of college reputations after policy changes or college responses to these changes, we choose instead to present the findings from the model described above, where outcomes are measured in years 25-30, ten simulation years after the onset of affirmative action policies. In the majority of affirmative action simulations, key dynamics have stabilized by this time. In the simulations using very strong policy magnitudes, where dynamics may not have stabilized, the simulation is stopped before a college’s quality ranking or selectivity decline by amounts that are almost certainly unrealistic. Still, given that we do permit college quality to update in every simulation year, a cautious reader may consider the findings from simulations using strong policy magnitudes as an upper bound on the effects of these policies on college enrollment over time.

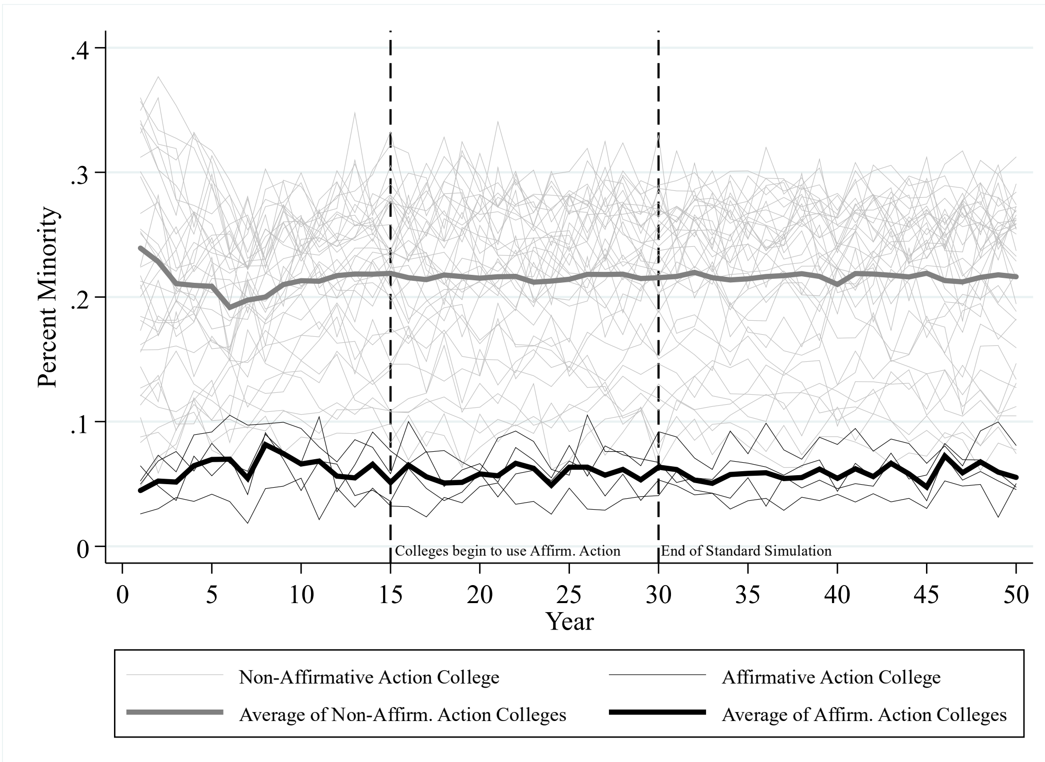
Affirmative action and recruitment magnitude ranges

The size of the affirmative action weights we use are based on our estimate of a 1.3 standard deviation relative race weight evident in selective admissions, described above in Appendix B. Given this estimate, we establish a "moderate" race-based affirmative action policy that gives a 0.75 standard deviation, or 150 points on our academic achievement scale, weight to Black or Hispanic students. Likewise, we assign a 300-point weight in a "strong" affirmative action policy. Thus, strong racial affirmative action is slightly stronger than the average currently used by highly selective colleges and moderate racial affirmative action is roughly half as strong.

Likewise, light, moderate, and strong SES-based affirmative action gives students an implicit weight of plus or minus 50, 100, or 150 points, respectively, for each standard deviation they are above or below the average student in resources. We chose these values to ensure that our simulations represent a range that encompasses significant increases over current practice in SES-based affirmative action, and thus present 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.

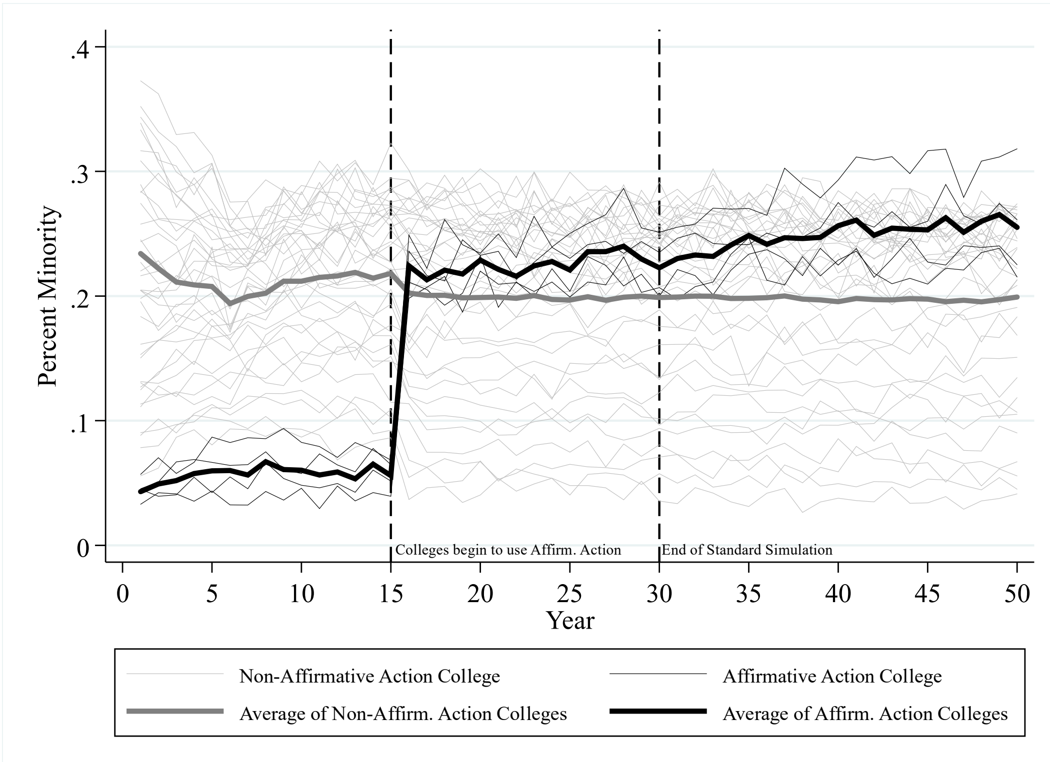
Recruitment magnitude values were selected to be comparable in magnitude to affirmative action policies that affect colleges' evaluations of students in our simulations. Because 50 points is roughly equivalent to half a standard deviation in the college quality distributions during baseline (i.e. no affirmative action or recruitment) simulation runs, we use values of 25, 50, and 100 to represent light, moderate, and strong recruitment magnitudes. This decision is justified in part by Brown and Hirschman (2006), whose evidence suggests that gains in applications from targeted minority student recruitment were roughly similar to losses in likelihood of admission after race-conscious affirmative action was banned in Washington.

Figure C1: Changes in Black and Hispanic Enrollment over Time with no Colleges Using Affirmative Action Policies



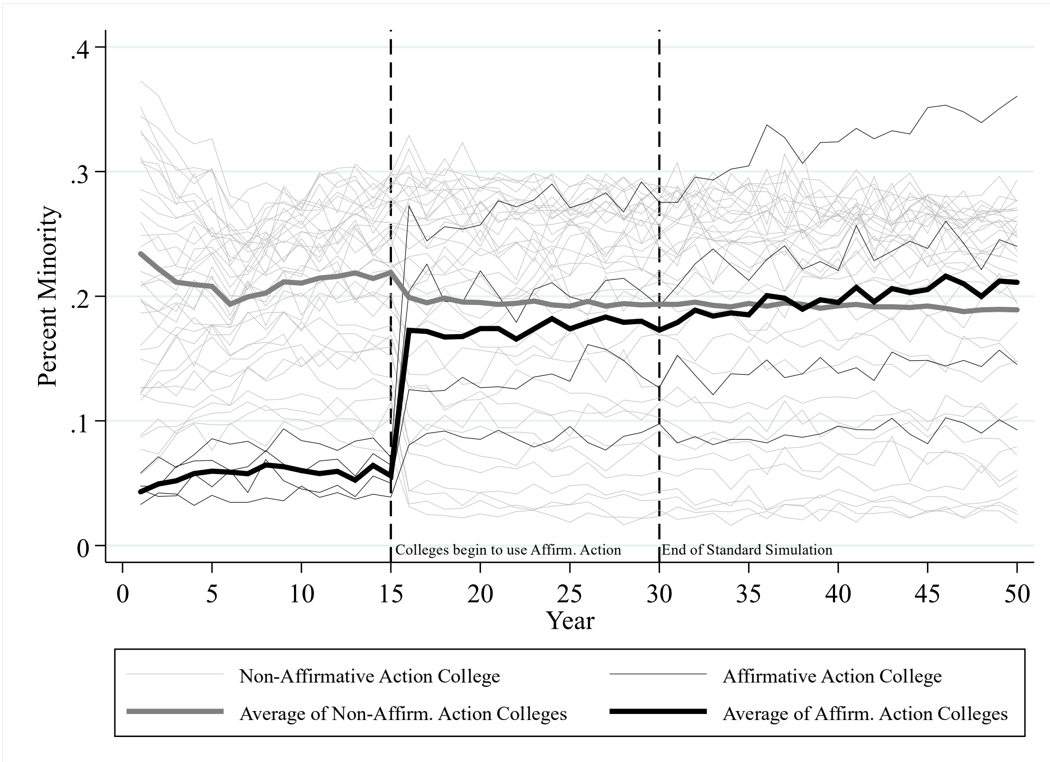
Notes: Figure C1 shows changes in Black and Hispanic enrollment for all colleges over time in a simulation where no colleges use affirmative action or recruiting. The thin black lines show enrollment for colleges that do, in other simulations, use affirmative action or recruitment. The thin, grey lines show Black and Hispanic enrollment for colleges that do not, and would not in other simulations, use affirmative action. The thick lines, one black and one grey, are weighted averages of the like-color thin lines. The figure also contains two dashed, vertical lines. The leftmost line indicates when schools would normally begin to use affirmative action or recruitment strategies. The rightmost line indicates the normal end period for a given simulation. Source: authors' simulations.

Figure C2: Changes in Black and Hispanic Enrollment over Time with Top 4 Colleges using “Real-World” Race-Based Affirmative Action



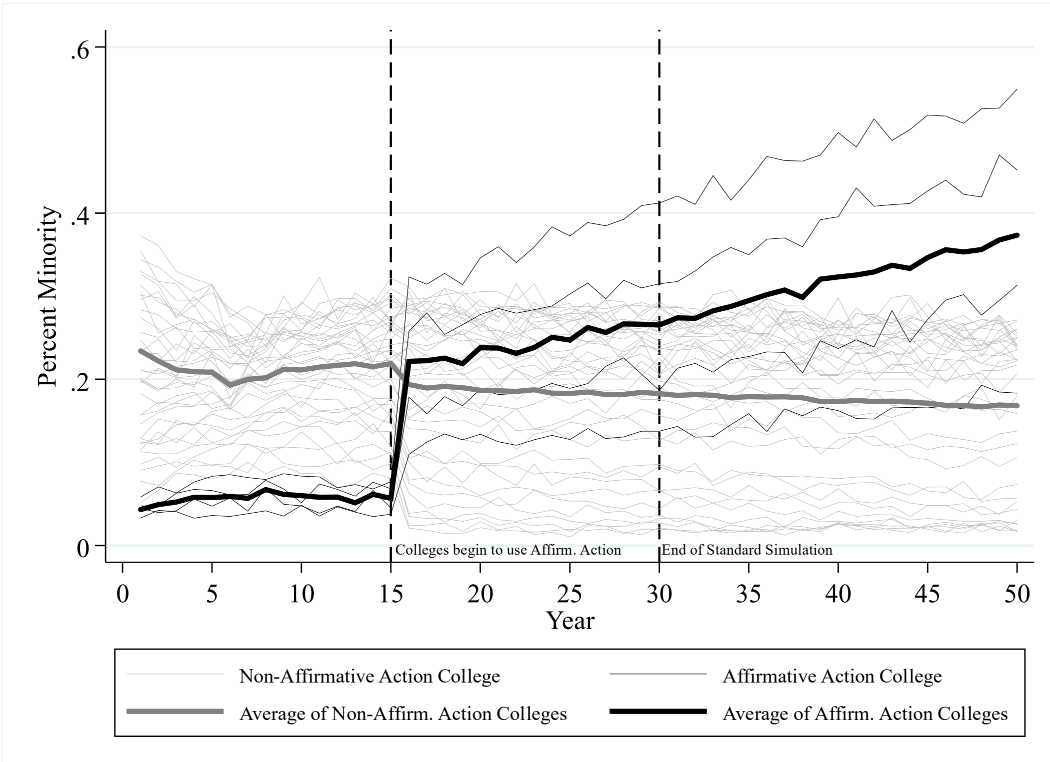
Notes: Figure C2 shows changes in Black and Hispanic enrollment for all colleges over time in a simulation where the top four schools use “real-world” race-based affirmative action, which corresponds to a weight of 260. The thin black lines show enrollment for colleges that use affirmative action. The thin, grey lines show Black and Hispanic enrollment for colleges that do not use affirmative action. The thick lines, one black and one grey, are weighted averages (by student enrollment) of the like-color thin lines. The figure also contains two dashed, vertical lines. The leftmost line indicates when the top four schools begin to use SES-based affirmative action. The rightmost line indicates the normal end period for a given simulation. Source: authors’ simulations.

Figure C3: Changes in Black and Hispanic Enrollment over Time with Top 4 Colleges using Moderate SES-Based Affirmative Action and Moderate Race-Based Recruiting



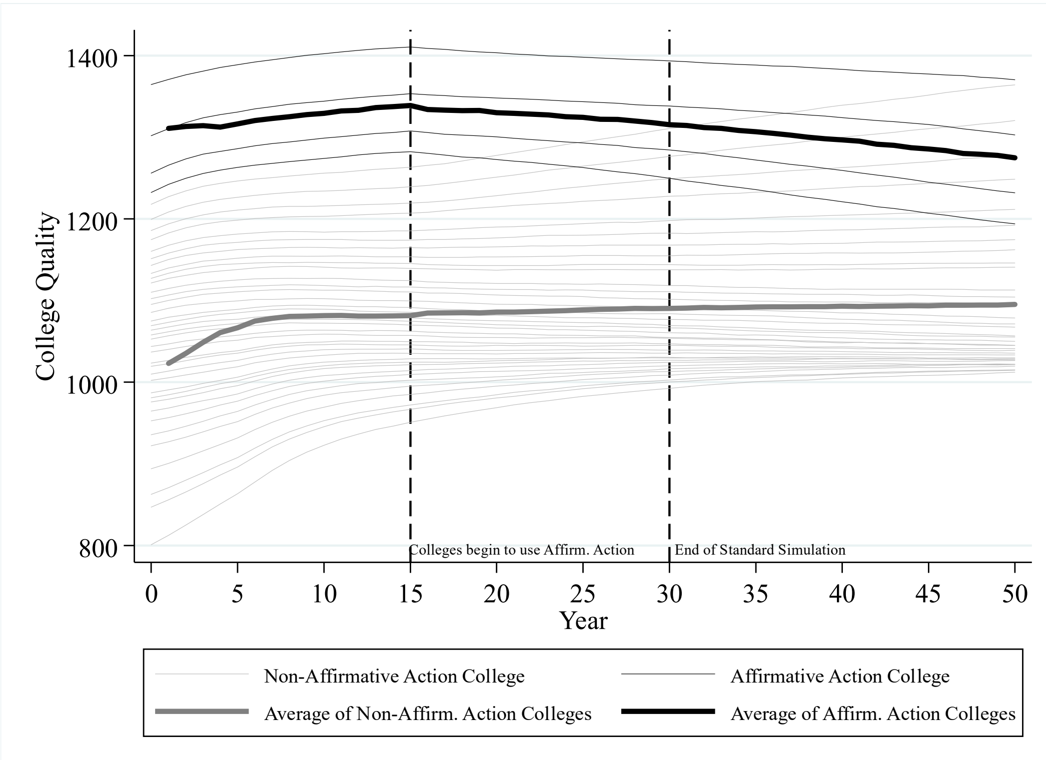
Notes: Figure C3 shows changes in Black and Hispanic enrollment for all colleges over time in a simulation where the top four colleges use moderate SES-based affirmative action and moderate race-based recruitment, which corresponds to a weight of 100 and 75, respectively. The thin black lines show enrollment for colleges that use affirmative action. The thin, grey lines show Black and Hispanic enrollment for colleges that do not use affirmative action. The thick lines, one black and one grey, are weighted averages (by student enrollment) of the like-color thin lines. The figure also contains two dashed, vertical lines. The leftmost line indicates when the top four schools begin to use race-based affirmative action. The rightmost line indicates the normal end period for a given simulation. Source: authors' simulations.

Figure C4: Changes in Black and Hispanic Enrollment over Time with Top 4 Colleges using Strong SES-Based Affirmative Action and Strong Race-Based Recruiting



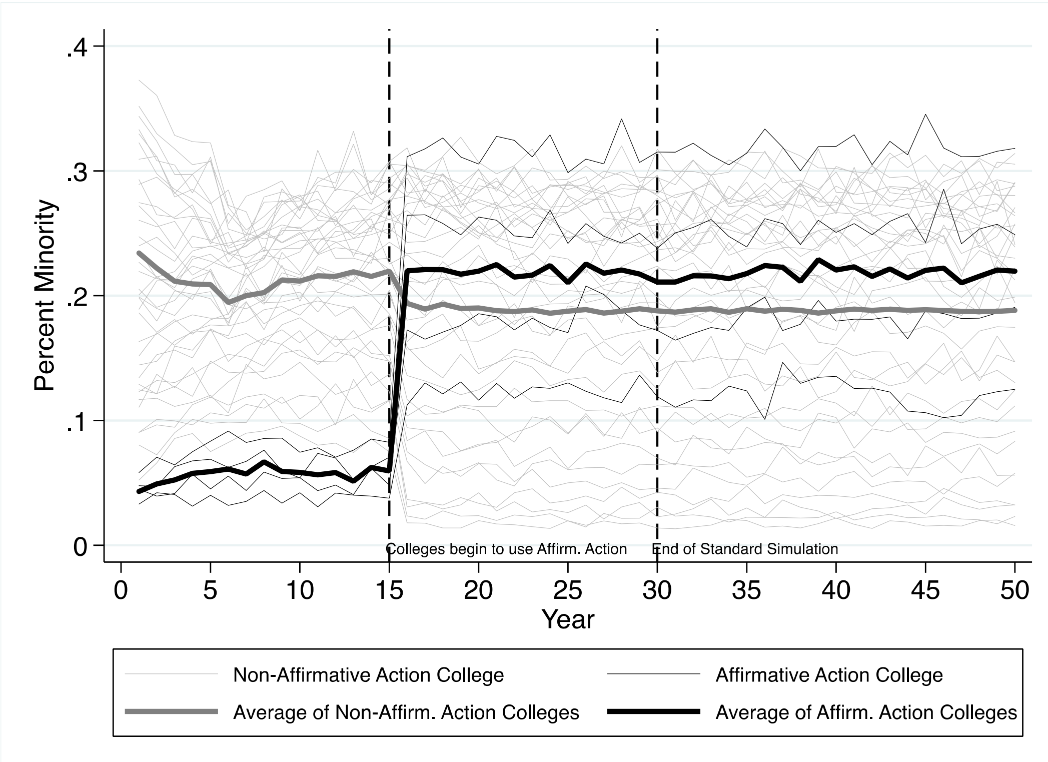
Notes: Figure C4 shows changes in Black and Hispanic enrollment for all colleges over time in a simulation where the top four colleges use strong SES-based affirmative action and strong race-based recruitment, which corresponds to a weight of 100 and 75, respectively. The thin black lines show enrollment for colleges that use affirmative action. The thin, grey lines show Black and Hispanic enrollment for colleges that do not use affirmative action. The thick lines, one black and one grey, are weighted averages (by student enrollment) of the like-color thin lines. The figure also contains two dashed, vertical lines. The leftmost line indicates when the top four schools begin to use race-based affirmative action. The rightmost line indicates the normal end period for a given simulation. Source: authors' simulations.

Figure C5: Changes in College Quality Rank over Time with Top 4 Colleges using Strong SES-Based Affirmative Action and Strong Race-Based Recruiting



Notes: Figure C5 shows changes in college quality rank for all colleges over time in a simulation where the top four colleges use strong SES-based affirmative action and strong race-based recruitment, which corresponds to a weight of 100 and 75, respectively. College quality is calculated as the five-year running average of enrolled student caliber. The thin black lines show quality for colleges that use affirmative action. The thin, grey lines show quality for colleges that do not use affirmative action. The thick lines, one black and one grey, are weighted averages (by student enrollment) of the like-color thin lines. The figure also contains two dashed, vertical lines. The leftmost line indicates when the top four schools begin to use race-based affirmative action. The rightmost line indicates the normal end period for a given simulation. Source: authors' simulations.

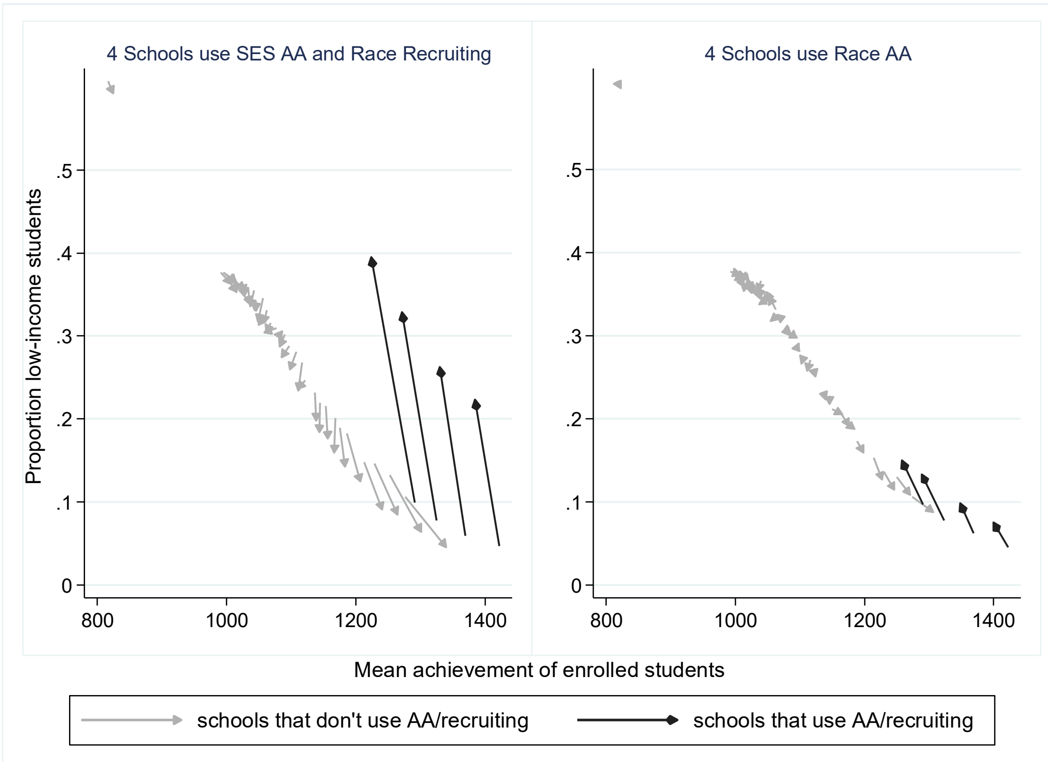
Figure C6: Changes in Black and Hispanic Enrollment over Time with Top 4 Colleges using Strong SES-Based Affirmative Action and Strong Race-Based Recruiting, College Quality Fixed after Year 15



Notes: Figure C6 shows changes in Black and Hispanic enrollment for all colleges over time in a simulation where the top four colleges use strong SES-based affirmative action and strong race-based recruitment, which corresponds to a weight of 100 and 75, respectively. Unlike the simulations for figures C1-C5, the quality ranking of colleges does not change in this simulation after year 15. The thin black lines show enrollment for colleges that use affirmative action. The thin, grey lines show Black and Hispanic enrollment for colleges that do not use affirmative action. The thick lines, one black and one grey, are weighted averages (by student enrollment) of the like-color thin lines. The figure also contains two dashed, vertical lines. The leftmost line indicates when the top four schools begin to use race-based affirmative action. The rightmost line indicates the normal end period for a given simulation. Source: authors' simulations.

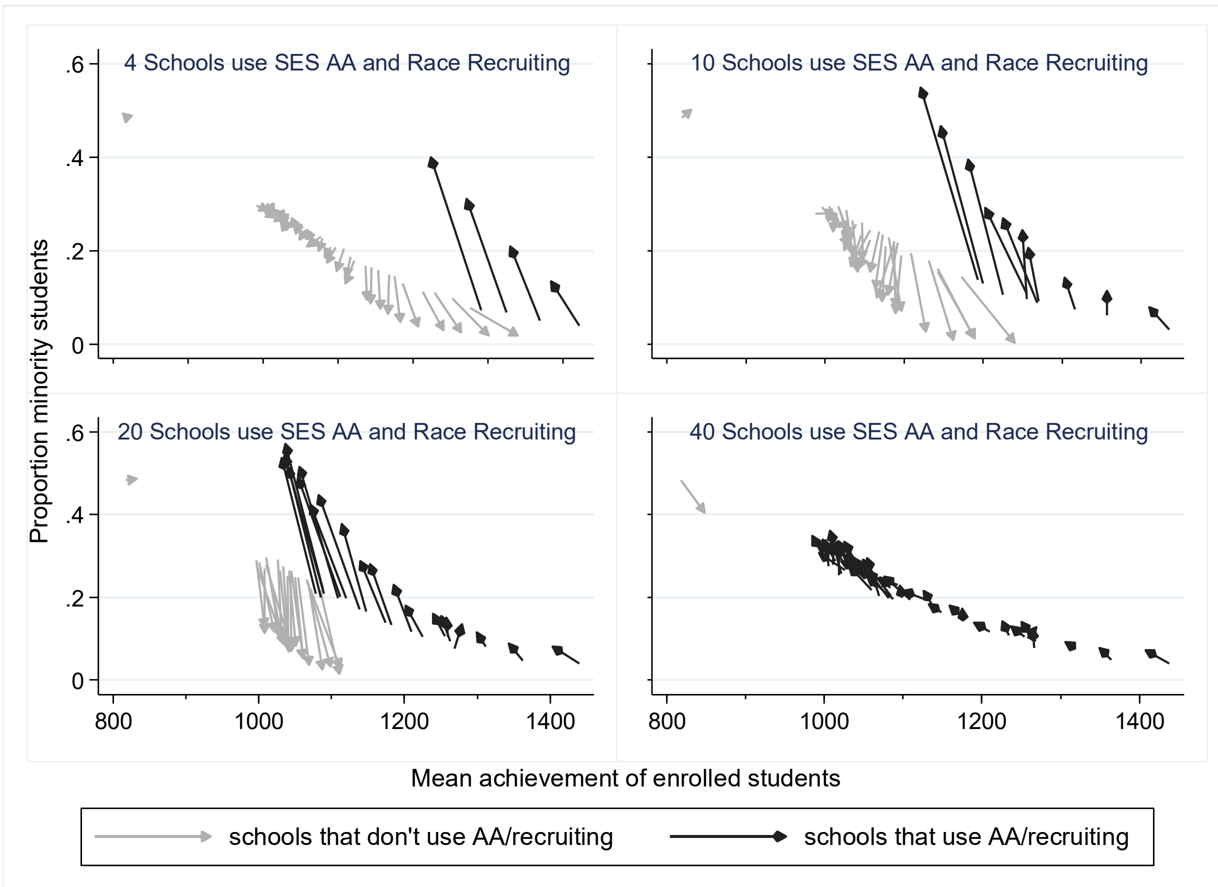
APPENDIX D. Effects of Affirmative Action Policies on Non-AA Schools

Figure D1. Mean achievement and proportion low-income by type of admission policies used by top four schools.



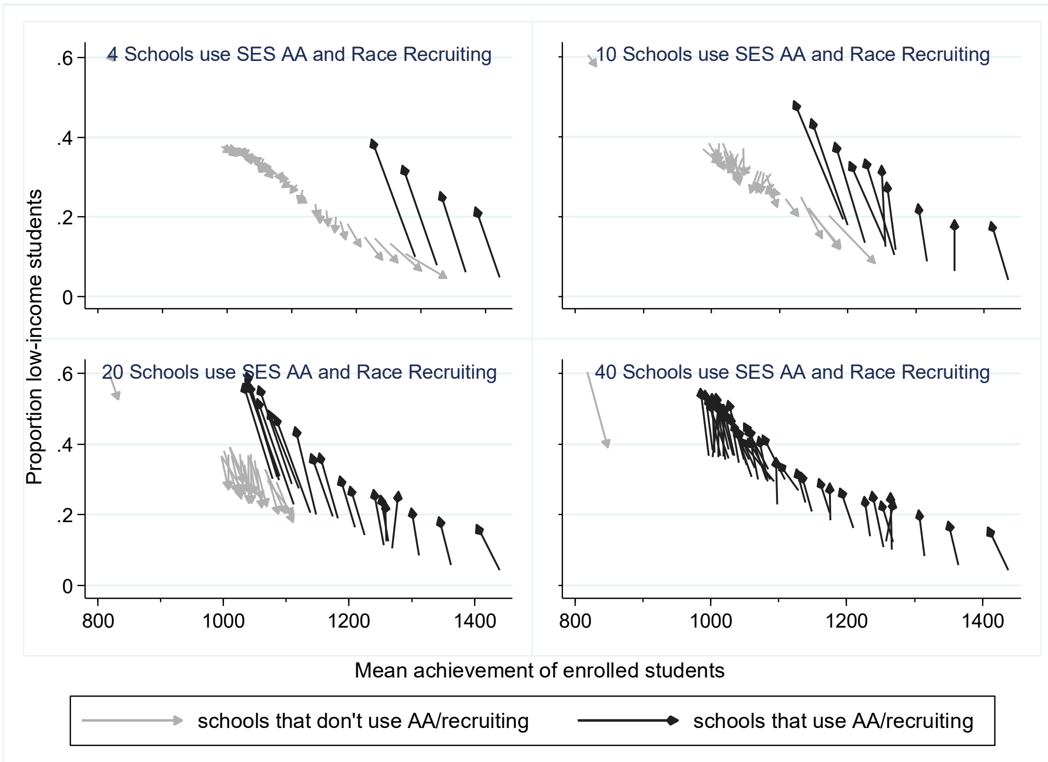
Notes. The left panel gives the results of the scenario where strong socioeconomic-based affirmative action and race-recruiting policies are used by the top four schools. The right panel gives the results of the scenario where the top four schools use strong race-based affirmative action policies. Arrows start at a school's position in year 15 when it was not using affirmative action, and end at the school's position in year 30. The left-most arrow captures students who do not enroll in college in our simulation. Source: authors' simulation.

Figure D2. The mean achievement and proportion minority by number of schools using admissions policies.



Notes. The figure gives the results of the scenario where strong socioeconomic-based affirmative action policies and race recruiting policies are used. Arrows start at a school's position in year 15 when it was not using affirmative action, and end at the school's position in year 30. The left-most arrow captures students who do not enroll in college in our simulation. SES is socioeconomic status. The left-most arrow captures students who do not enroll in college in our simulation. Source: authors' simulation.

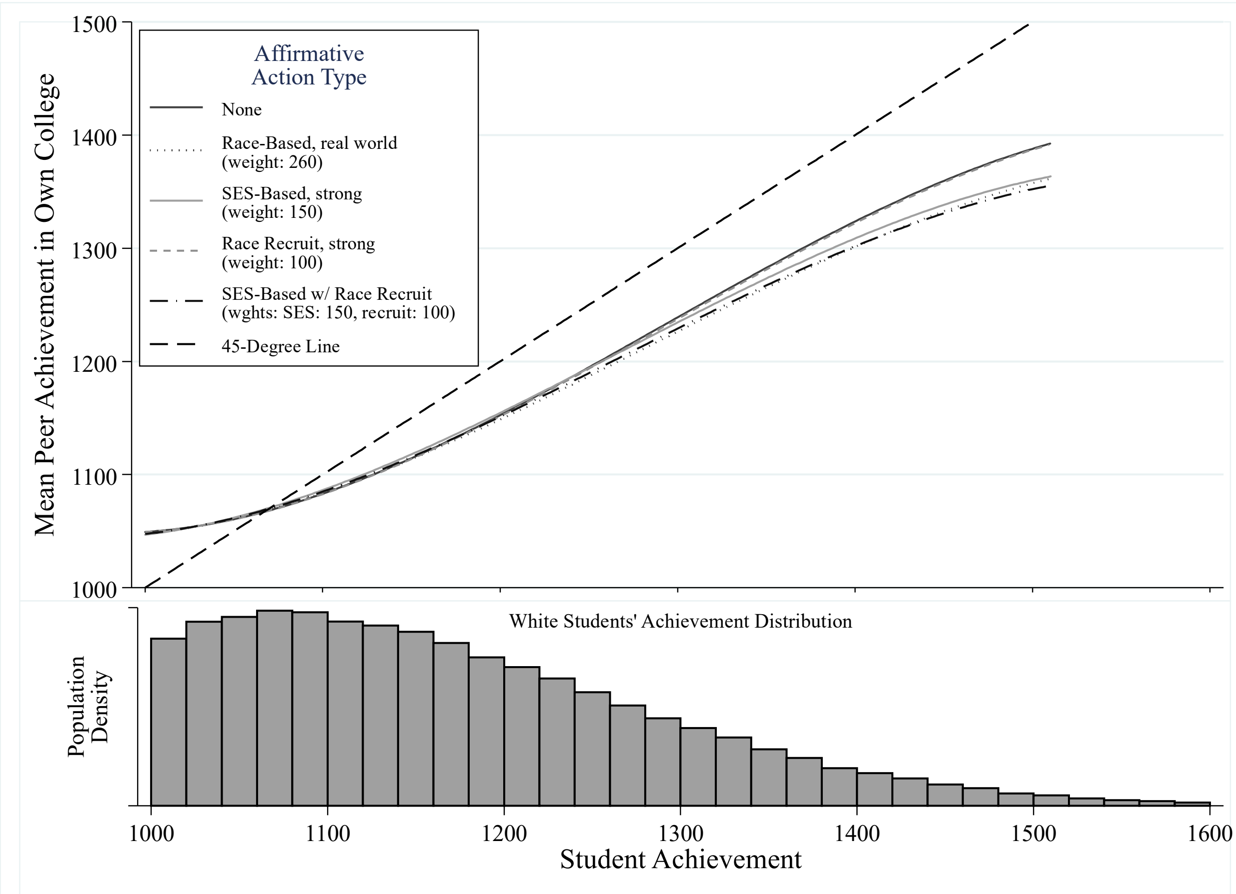
Figure D3. The mean achievement and proportion low-income by number of schools using affirmative action.



Notes. The figure gives the results of the scenario where strong socioeconomic-based affirmative action policies and race recruiting policies are used. Arrows start at a school's position in year 15 when it was not using affirmative action, and end at the school's position in year 30. The left-most arrow captures students who do not enroll in college in our simulation. SES is socioeconomic status. The left-most arrow captures students who do not enroll in college in our simulation. Source: authors' simulation.

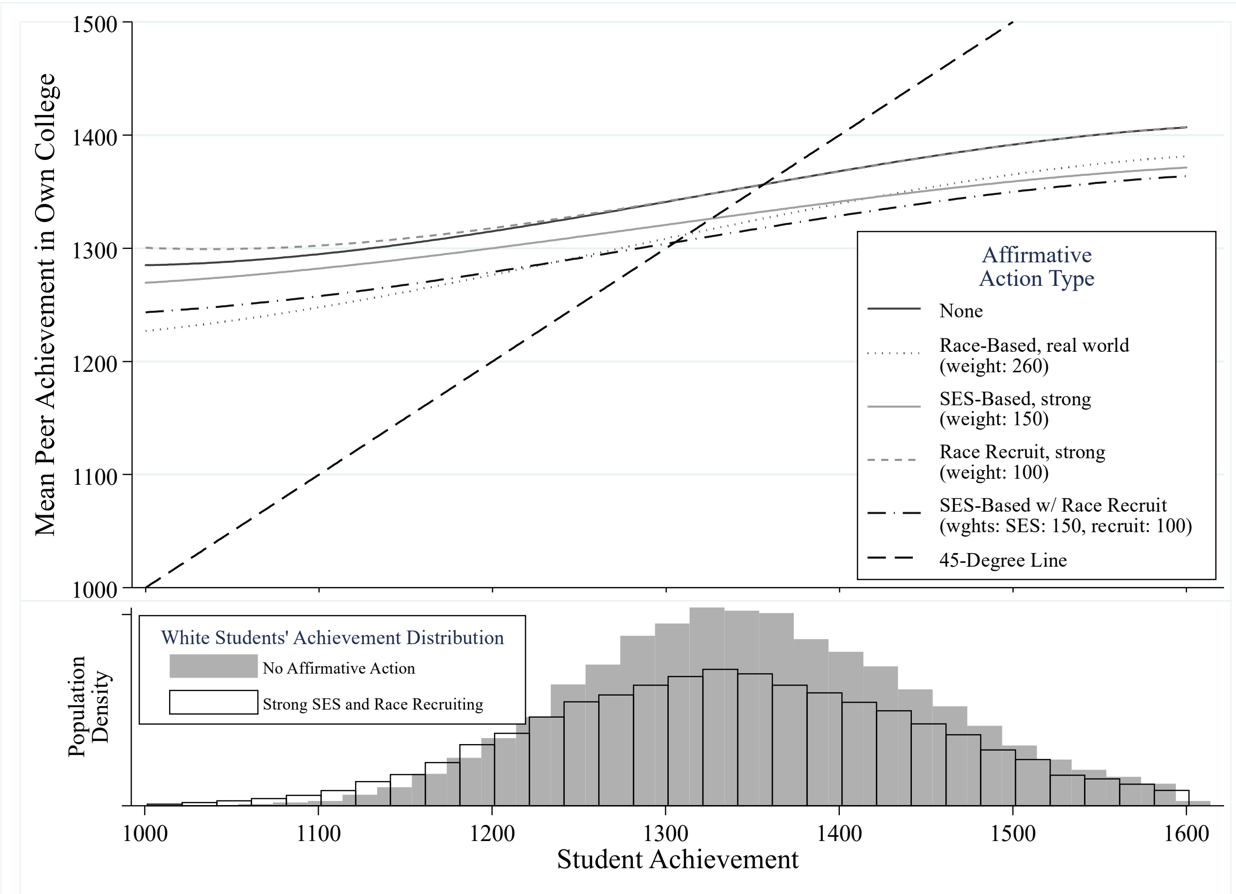
APPENDIX E

Figure E1. Mean achievement of White students' college classmates, by own achievement, and affirmative action type; results from all schools; top four ranked schools use affirmative action.



Source: authors' simulation.

Figure E2. Mean achievement of White students' college classmates, by own achievement, and affirmative action type; results from top four ranked schools; top four ranked schools use affirmative action.



Source: authors' simulation.