UNITED STATES DISTRICT COURT
FOR THE DISTRICT OF MASSACHUSETTS

STUDENTS FOR FAIR ADMISSIONS, INC., *Plaintiff*, v. PRESIDENT AND FELLOWS OF HARVARD COLLEGE (HARVARD CORPORATION), *Defendant*.	Civil Action No. 1:14-cv-14176

REPORT OF DAVID CARD, Ph.D.

December 15, 2017

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1. QUALIFICATIONS

1. I received a B.A. degree in Economics from Queen's University (in Canada) in 1978 and a Ph.D. in Economics from Princeton University in 1983. From 1982 to 1983, I was an Assistant Professor at the University of Chicago Graduate School of Business. From 1983 to 1997, I held positions as Assistant Professor and Professor of Economics at Princeton University. Since 1997, I have been the Class of 1950 Professor of Economics at the University of California, Berkeley.

2. I have published more than 110 articles and book chapters, co-authored one book, and co-edited seven others, including the *Handbook of Labor Economics.* The majority of my publications are focused on labor economics—the field of economics that addresses questions related to discrimination in various contexts, including education. My articles have appeared in the leading journals in economics and econometrics, including *Econometrica*, the *American Economic Review*, the *Quarterly Journal of Economics*, the *Journal of Political Economy*, and the *Journal of Econometrics*. I served as co-editor of the *American Economic Review* from 2002 to 2005 and co-editor of *Econometrica* from 1993 to 1997. I have also served on several editorial boards and government advisory committees for statistical issues, including the National Academy of Science Committee on National Statistics (2012 – 2015), the U.S. Census Advisory Committee (1991 – 1996), Statistics Canada's Labour Statistics Advisory Committee (1990 – 2002), and the National Institutes of Health Social Sciences, Nursing, Epidemiology, and Methods Review Panel (1998 – 2003).

3. My research has been recognized by several awards and prizes, including election as a Fellow of the American Academy of Arts and Sciences in 1998, a Fellow of the Econometric Society in 1992, and a Fellow of the Society of Labor Economics in 2004. In 1995, I received the John Bates Clark Medal, widely regarded as one of the highest honors in the field of economics, which is awarded by the American Economic Association to the outstanding economist in the United States under the age of 40. In 2006, I was awarded the IZA Prize by the Institute for the Study of Labor in Bonn for outstanding academic achievement in the field of labor economics. In 2008, I was awarded the Frisch Medal by the Econometric Society for the best article in applied economics published in *Econometrica* in the previous two years. I was the co-recipient of the 2015 BBVA Foundation Frontiers of Knowledge Award in economics.

4. My research focuses on statistical analysis of the labor market and related data pertaining to such issues as wages, hours of work, employment, education, and immigration. I have published multiple studies analyzing differential labor-market outcomes across race and gender (including questions of discrimination), as well as a study of the effects of race-conscious admissions. In my capacity as a journal editor, member of an editorial board, and member of proposal review

committees, I have also edited, refereed, and critiqued many studies that address questions of discrimination, education, and/or college admissions. My complete CV, which includes a list of publications I have authored within the past ten years, is attached in Appendix A.

5. I am being compensated at my standard billing rate of $750 per hour. I have been assisted in this matter by staff of Cornerstone Research, who worked under my direction. In addition to compensation at my hourly rate, I receive compensation from Cornerstone Research based on its collected billings for supporting me in this matter. None of my compensation in this matter is in any way contingent or based on the content of my opinion in this or any other matter or the outcome of this or any other matter. A list of my testimony in the last four years is attached in Appendix A.

2. ASSIGNMENT AND SUMMARY OF OPINIONS

2.1. Assignment

6. Harvard's counsel have asked me to assess the following questions related to Harvard's admissions process, which I understand are relevant to the claims of the Plaintiff, Students for Fair Admissions, Inc. ("SFFA"), in this matter on the basis of the complaint and SFFA's expert reports:

- Does statistical evidence support SFFA's claim that Harvard discriminates against Asian-American applicants in undergraduate admissions decisions?

- Does statistical evidence support SFFA's claim that race is the determinative factor in undergraduate admissions decisions for many applicants?

- Is there statistical evidence that Harvard has engaged in racial balancing in its undergraduate admissions process?

- How would the racial composition and other attributes of Harvard's admitted class be expected to change if Harvard stopped considering race and instead pursued a variety of race-neutral ways of seeking to increase the racial diversity of its admitted class?

- Are the analyses and conclusions offered by SFFA's experts reliable?

7. In attempting to answer these questions, I have relied on several sources of information, including deposition testimony in this matter, documents produced by Harvard in this matter, database information produced by Harvard in this matter (covering all applicants to the classes of 2014 to 2019),[1] College Board data on neighborhood and high school demographics and high school quality produced in this matter, relevant public information and data, and academic research. I have also reviewed the reports submitted by SFFA from Professor Peter Arcidiacono and Mr. Richard

[1] Prof. Arcidiacono states that the list of data Harvard produced and omitted can be found at HARV00006413, HARV00006471, HARV00006541, HARV00006607, HARV00006695, and HARV00006759. A list of additional database fields produced by Harvard is available at HARV00001322 – HARV00001361.

Kahlenberg and their relevant supporting materials.[2]

8. Appendix B to this report lists the documents on which I relied in forming the opinions expressed in this report.

2.2. Overview of report and summary of findings

9. SFFA's Complaint[3] and expert reports claim that Harvard's undergraduate admissions decisions exhibit bias against Asian-American applicants, that race is a determinative factor in the Harvard admissions process for many applicants, and that Harvard can achieve its diversity goals without considering race by using a variety of race-neutral admissions practices.

10. SFFA's claim of discrimination against Asian-American applicants relies most fundamentally on the premise that Asian-American applicants are admitted at a lower rate than White applicants, while possessing higher academic credentials than White applicants on average. As I explain in this report, however, there is a critical flaw in SFFA's reasoning: as I understand from my review of the documents and testimony in this matter, and as my empirical analysis corroborates, Harvard's admissions process values many dimensions of excellence, not just prior academic achievement.

11. As I detail in **Section 3** below, Harvard's applicant pool is full of students with outstanding academic credentials. More than 8,000 applicants for the class of 2019 had perfect GPAs, approximately 3,500 applicants had perfect SAT math scores, and nearly 1,000 applicants had perfect ACT and/or SAT composite scores. In that pool, having strong academic credentials is not sufficient to make an applicant a strong candidate for admission. The record in this case makes clear that it is often the non-academic aspects of a candidate's application that determine whether the candidate is admitted from this academically exceptional pool, that the evaluation of each candidate takes into account the full context of his or her life experiences, and that Harvard's ultimate goal is to admit a student body that exhibits excellence in a variety of forms and includes students with diverse experiences, backgrounds, skills, and interests. Harvard's admissions data are consistent with these facts. They show, for example, that candidates who are strong on dimensions other than academics are rarer than academically strong candidates. They also show that candidates who receive high ratings in at least three of the four categories rated by admissions officers (academic, extracurricular, athletic, and personal)—referred to in this report as candidates who are "multi-dimensional"—have a

[2] Expert Report of Peter S. Arcidiacono, *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College*, October 16, 2017 ("Arcidiacono Report"); Expert Report of Richard D. Kahlenberg, *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College*, October 16, 2017 ("Kahlenberg Report").

[3] Complaint, *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College (Harvard Corporation); and the Honorable and Reverend the Board of Overseers*, November 17, 2014 ("Complaint").

high admission rate and compose a much larger share of the admitted class than candidates who are exceptional on just one dimension.

12. Prof. Arcidiacono reveals a significant misunderstanding of Harvard's admissions process by focusing so much of his analysis on academic achievement. For example, four of the six regression models that Prof. Arcidiacono offers do not include controls for the three non-academic ratings (extracurricular, personal, and athletic), which are central to Harvard's evaluation of candidates for admission. And Prof. Arcidiacono accounts in only a crude and limited way for considerations of high school quality and socioeconomic background that Harvard uses to place in context each applicant's prior academic achievement. Such analyses are fundamentally flawed and unreliable because they fail to account for the multi-dimensional evaluation Harvard employs when rendering its admissions decisions.

13. As I explain in **Section 4,** Prof. Arcidiacono attempts to justify his focus on academics by presenting a variety of basic descriptive analyses that purport to show a broad correlation between Harvard's academic index and non-academic qualifications that Harvard considers. He then argues that it is reasonable to assume that Asian-American applicants are stronger than applicants of other races in non-academic respects (including factors he cannot measure and include in his model) because they are stronger on academic measures. That is a central assumption of his analysis—and, as I demonstrate in **Section 4**, it is wrong. A more careful examination of the data shows that White applicants are stronger than Asian-American applicants, in aggregate, across the three non-academic dimensions that Harvard rates (athletic, extracurricular, and personal), and that they are more likely to exhibit multi-dimensional excellence (i.e., receive high ratings in at least three of the four categories). In fact, Prof. Arcidiacono's own analysis shows that, across all of the non-academic variables he includes in his regression model, White applicants in aggregate are stronger than Asian-American applicants. Because non-academic factors are much harder to quantify than academic factors, and thus fewer of them are observable in the Harvard admissions database, there is a strong possibility that statistical models like those developed by Prof. Arcidiacono will exclude important non-academic factors, and will therefore be biased in favor of finding a race-based disparity in admissions between Asian-American and White applicants. That is, it is quite possible that if one could control more extensively for non-academic factors, those factors—and not race—would explain any disparity in the admission rate between Asian-American and White applicants.

14. In **Section 4**, I also explain how Prof. Arcidiacono's models include very little information that can account for the overall context of each candidate's application, such as the quality of the applicant's high school, the applicant's socioeconomic circumstances, and the resources and opportunities available to the applicant as a result of his high school, neighborhood, and family background. This contextual information is critical in the admissions process, because

Harvard recognizes that one cannot evaluate a student's grades, standardized test scores, or other attributes without understanding the circumstances in which the applicant grew up. For that reason, the admissions process is designed to ensure that admissions officers have detailed knowledge of many of the high schools and neighborhoods from which applicants apply, and that admissions officers examine each applicant's file in light of that context. Importantly, as I show below in Section 4, Prof. Arcidiacono failed to make use of a variety of such contextual factors that were available in data produced to him, and that differ on average between Asian-American and White applicants.

15. In **Section 5**, I turn to a more formal statistical analysis of the difference in admission rates between White and Asian-American applicants. This analysis shows that the purported "penalty against Asian Americans" identified by Prof. Arcidiacono does not actually exist.[4] Prof. Arcidiacono's finding is instead driven by two limitations of his model.

16. First, as noted above, his model does not account for numerous critical factors in the available data that provide important context for each application, including measures of applicants' socioeconomic status (such as the demographics of their neighborhoods), the quality of their high schools, and other variables that can reflect differences in life experiences and opportunities. Prof. Arcidiacono's own models show that the factors of this type that he does include in his model help explain the disparity in admission rates between White and Asian-American applicants, which is why it is problematic that Prof. Arcidiacono does not control for more of them. Once Prof. Arcidiacono's model is modified to account for these additional factors, it finds no evidence of a racial disparity in admissions decisions.

17. Second, Prof. Arcidiacono's model combines data from multiple admissions cycles, thus imposing the assumption that Harvard compares applicants *across* years rather than simply within each year's application pool. As I detail below, that assumption is unreasonable. Each admissions cycle is different, and the data confirm as much, showing that the estimated effect of various factors on an applicant's probability of admission changes substantially from year to year. Importantly, when I analyze the data year-by-year, as the evidence supports, I find that the model's predictive accuracy increases. My year-by-year analysis finds that the estimated effect of Asian-American ethnicity on applicants' probability of admission is not statistically significant in *any* year, or even on average across all six years, and is actually *positive* in four of six years.

18. It is important to note that even when I enrich the model to account for additional control variables and to account for differences in the admissions process from year to year, the model still does not perfectly capture all of the information on which the Harvard Admissions Committee relies when making admissions decisions. This problem is what I refer to throughout the report as a

[4] Arcidiacono Report, p. 61.

"missing data" problem—a problem that exists when modeling any complex decision process (like admissions to Harvard) in which decisionmakers consider many factors that are hard to quantify. The data I am discussing are "missing" because they are not quantified in Harvard's database or because they are inherently difficult to quantify. Importantly, because non-academic factors that are a relative strength of White applicants (on average) are harder to quantify than academic factors, it is likely that additional such factors remain missing from the model even after I enrich the model to capture more information on non-academic factors.

19. In **Section 5,** I also address Prof. Arcidiacono's claim that Harvard's personal and overall ratings are biased against Asian-American applicants. In the case of the personal rating, the statistical evidence Prof. Arcidiacono offers in support of this claim is weak for two key reasons. First, the ordered logit models that Prof. Arcidiacono uses to try to isolate the effect of race on the personal rating are, by his own measure of statistical reliability, weak—that is, the models explain only a relatively small fraction of the differences across candidates in the personal ratings. A key reason for this is that the available admissions data include only a few quantitative variables that can be used to model variation in the personal rating. In essence, the "missing data" problem I describe above is particularly severe for the assessment of personal ratings, which depend largely on qualitative factors that cannot be captured in Harvard's database. For example, testimony in the record indicates that the applicant's essay is an important consideration in the personal rating, but there is no quantifiable measure of the essay in the data I analyze. This means that the disparity Prof. Arcidiacono labels "bias" may very well be explained by factors other than race that the model does not include. Importantly, Prof. Arcidiacono's own model finds that the estimated negative effect of Asian-American ethnicity on the personal rating shrinks as non-academic factors are added to the model. This pattern suggests that the estimated effect would shrink further if one could quantify the missing data that the Harvard admissions officers use to form their assessments.

20. Another reason to be skeptical of the reliability of Prof. Arcidiacono's model of the personal rating is that his model of the academic rating—which is the most reliable of any of his ratings models—shows that Asian-American ethnicity has an estimated *positive* and significant effect on that rating. So does his model of the extracurricular rating. Given these results, one of two things must be true. Either (1) Harvard is engaging in an exceptionally unusual form of discrimination, in which it is *favoring* Asian-American applicants in the academic and extracurricular ratings only to penalize them in the personal and overall ratings, or (2) Prof. Arcidiacono's ratings models are simply not reliable enough to measure all of the differences between Asian-American and White applicants on the various dimensions valued by Harvard that drive the assignment of ratings.

21. While Prof. Arcidiacono provides no reliable evidence that the personal rating is biased against Asian-American applicants—and while excluding that rating from a model of admissions is

problematic because the rating plays a significant role in the admissions process and incorporates data on the qualities of the applicants that are otherwise missing—I agree with Prof. Arcidiacono that the *overall* rating should be excluded from the model. Testimony in this case indicates that an applicant's race may have a direct effect on her overall rating, and it is a well-accepted statistical practice to exclude variables from a regression model that may themselves be directly influenced by the variable of interest (here, race). While I have excluded the overall rating from my admissions model, I also believe that the model of overall ratings developed by Professor Arcidiacono is too weak to provide reliable statistical evidence of "bias" in the assignment of this rating. Like Prof. Arcidiacono's models of the ratings in general, the overall-rating model leaves unexplained a large proportion of the variation in the overall ratings and cannot control for numerous factors that may influence the overall rating and may be correlated with race.

22. Despite my view that removing the personal rating from the model is a flawed approach, I also implement an analysis that assumes for the sake of argument that the personal rating may be biased and removes it (as well as the overall rating) from the model altogether. This is an extremely conservative approach, because it removes the personal rating from the model entirely—not just the supposedly biased component of the rating—even though Prof. Arcidiacono's own analysis shows that, when the supposed bias is statistically eliminated from the personal rating, White applicants' personal ratings are *still* on average slightly higher than those of Asian-American applicants. Nevertheless, using this very conservative model, I still find no evidence of a statistically significant negative association between Asian-American ethnicity and applicants' likelihood of admission in five of the six admissions cycles for which data are available.

23. In **Section 6,** I assess how the race of African-American, Hispanic, and Other (non-Asian) minority race (AHO) candidates affects their likelihood of admission, in order to respond to Prof. Arcidiacono's argument that race has a large effect for such candidates.[5] I reach several conclusions on this issue. First, consistent with testimony from Harvard witnesses, I find that although AHO ethnicity is associated with a significantly higher likelihood of admission, the importance of race in explaining admission decisions is much smaller than that of many other factors Harvard considers. Second, I show that race plays only a small role in admissions outcomes for the vast majority of applicants. And for the small number of applicants for whom race plays a more significant role, other non-race factors also substantially affect the applicants' likelihood of admission. Third, I find that the estimated effect of race for almost all AHO applicants is smaller than that of individualized "unobservable" factors that cannot be quantified by a statistical model. Taken together, these results suggest that, while race plays a role in admission decisions—by design—it is just one of many factors

[5] Other minority race applicants include applicants classified as Native American or Hawaiian/Pacific Islander under Harvard's "old methodology," the race definition that Prof. Arcidiacono uses throughout his report (Arcidiacono Report, p. 23).

Harvard considers in its whole-person review of each candidate. I also examine Prof. Arcidiacono's claim that Harvard has recently imposed a floor on the admission rate of African-American applicants and find no evidence to support that claim.

24. In **Section 7,** I turn to a final question: are there race-neutral admissions practices that Harvard could implement that would allow it to achieve its diversity objectives, without lowering the quality of its class on other dimensions that it values? Using the admissions model developed in Section 5, I simulate how various race-neutral admissions practices (both alone and in combination) would affect the demographic and other characteristics of the admitted class. I show that Harvard *could* achieve comparable ethnic and racial diversity by other means, but that doing so would produce a student body that is less exceptional on multiple dimensions that I understand Harvard values (such as academic credentials, extracurricular achievement, and personal qualities).

25. In performing my analysis in **Section 7**, I also assess the literature analyzed and simulations offered by Mr. Kahlenberg. I generally agree with Mr. Kahlenberg that race-neutral alternatives can sometimes be used to help universities increase racial diversity. As I explain below, however, the relevant question here is not whether *some* universities could achieve diversity without considering race but whether *Harvard* could do so, and furthermore whether doing so would harm Harvard's other institutional and educational objectives. A direct analysis of Harvard's data is needed to answer that question. With regard to Mr. Kahlenberg's simulations of race-neutral alternatives, I show using Mr. Kahlenberg's own data that the proposed alternatives he considers either lead to a significantly less diverse class, or to a class that is comparably diverse but far weaker in other dimensions that I understand Harvard values, such as academic quality.

3. AN OVERVIEW OF HARVARD'S APPLICANT POOL AND ADMISSIONS PROCESS

26. The first step in my analysis is a careful review of the discovery in this case concerning Harvard's admissions process. The purpose of this review is to understand what factors Harvard values when admitting students. As noted above, SFFA's claim of bias against Asian-American applicants relies centrally on the premise that Asian-American applicants have the strongest academic qualifications on average across racial groups, but are admitted at a lower rate than applicants of other races. SFFA's expert, Prof. Arcidiacono, focuses much of his analysis on academic qualifications. It is essential, however, to understand what *other* factors Harvard considers when evaluating candidates, and how important those factors are relative to academic credentials in explaining the variability in admissions outcomes.

27. In the remainder of this section, I summarize the key features of Harvard's decisionmaking process. I start with an analysis of the size of Harvard's applicant pool and the competitive nature of admissions decisions. I show that superb standardized test scores and GPAs are abundant among Harvard applicants, with thousands of candidates having perfect GPAs and/or SAT and ACT scores. It is impossible for Harvard to admit all applicants with exceptional academic credentials, and so focusing too much on such credentials when trying to understand admissions decisions (as Prof. Arcidiacono does) is the wrong approach.

28. I then summarize relevant information in the record that identifies the broader set of characteristics that Harvard seeks in the students it admits. Documents and testimony show that Harvard values candidates who can contribute to both academic and non-academic dimensions of campus life, and that Harvard considers the full context of an applicant's life experience (including the quality of her high school, the characteristics of her home neighborhood, and her family background) when deciding whom to admit. Those facts will be critical to the statistical analyses I offer in Sections 4 and 5. An important difference between my analysis and Prof. Arcidiacono's is that my analysis includes a much richer set of control variables, including more detailed controls for applicants' socioeconomic status (as measured by the demographic characteristics of their neighborhoods and high schools as well as their parents' occupations) that more accurately reflect and account for the many different factors Harvard weighs in its whole-person admissions process.

3.1. Harvard's admissions process is highly competitive, and academic achievement is abundant in its applicant pool

29. Harvard's admissions process is one of the most competitive and selective in the country. For example, more than 37,000 high school students applied to Harvard for admission to the class of

2019, but only 2,003 were admitted, leading to an admission rate of 5.37%.[6] According to U.S. News and World Report, Harvard had the third-lowest admission rate among U.S. universities in Fall 2016.[7]

30. Exhibit 1 shows the number of domestic applicants, number of domestic admitted students, and the admission rate to Harvard for domestic applicants each year for the classes of 2014 to 2019 (the years for which admissions data were produced in this matter).[8] As the table shows, Harvard's domestic applicant pool has grown since the class of 2014 admissions cycle, while the number of admitted domestic students has fallen, making Harvard's admissions process for domestic students even more competitive in recent years. More domestic candidates now apply each year for fewer spots, and as a result Harvard's admission rate has declined consistently over time from 8.75% to 6.61%.

Exhibit 1

Domestic applicants, admitted students, and admission rates at Harvard by year

	Class	Number of Applicants	Number of Admitted Students	Admission Rate
1.	**2014**	22,669	1,984	8.75%
2.	**2015**	26,071	1,920	7.36%
3.	**2016**	25,068	1,829	7.30%
4.	**2017**	25,117	1,804	7.18%
5.	**2018**	25,208	1,775	7.04%
6.	**2019**	26,568	1,756	6.61%
	Total	**150,701**	**11,068**	**7.34%**

Source: Arcidiacono Data

Note: Data are from applicants to the classes of 2014 – 2019 using Professor Arcidiacono's expanded sample.

[6] The admission rate of 5.37% includes all applicants and admitted students, including international students. Analyses in the remainder of this report are limited to domestic applicants, consistent with Prof. Arcidiacono's definition (see workpaper).

[7] U.S. News and World Report, "Top 100 Lowest Acceptance Rates," available at https://www.usnews.com/best-colleges/rankings/lowest-acceptance-rate, accessed December 7, 2017.

[8] I follow Prof. Arcidiacono by defining "domestic" applicants as those who are U.S. citizens or permanent residents, and in limiting my analyses to domestic applicants. Throughout my analyses, I primarily rely on Prof. Arcidiacono's produced, processed dataset (the "Arcidiacono Data"), which is constructed using the data produced by Harvard in this litigation. I also use a version of Prof. Arcidiacono's produced dataset that is augmented with additional variables from the College Board and Harvard's underlying data and that reflects a few technical corrections, which I refer to as the "Augmented Arcidiacono Data."

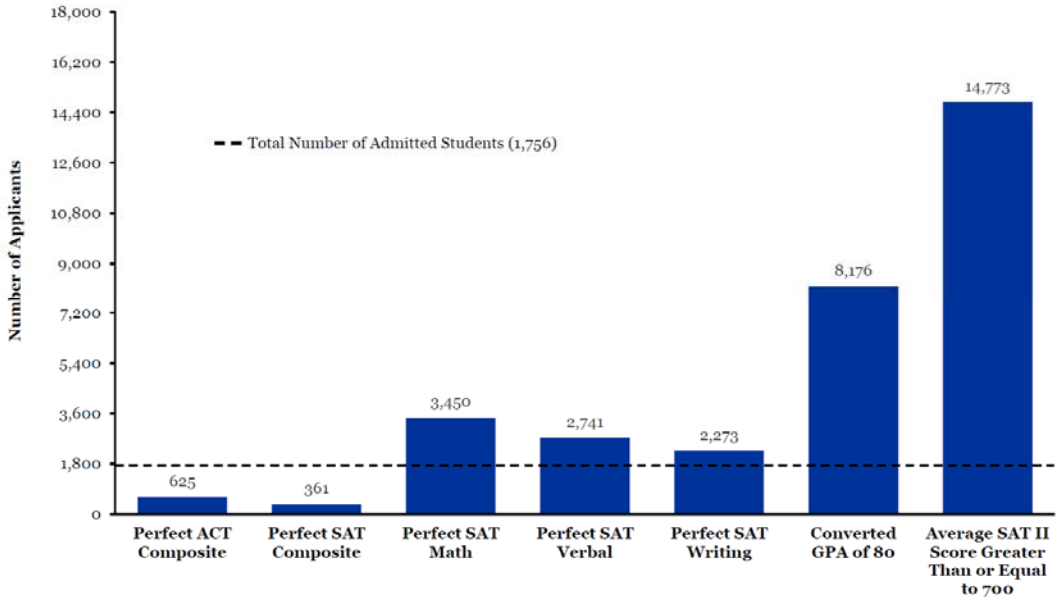
31. In addition to having a relatively small number of places available in its freshman class for a large number of applicants, Harvard also has an applicant pool with extraordinary academic qualifications. As shown in Exhibit 2, nearly 3,500 domestic applicants to the class of 2019 had perfect math SAT scores. Additionally, more than 8,000 domestic applicants had a perfect converted GPA (based on Harvard's GPA index, which normalizes GPAs across high schools), 625 earned perfect composite ACT scores, 361 earned a perfect 2400 on the SAT, and thousands had average SAT subject test scores of 700 or higher. As shown in Exhibit 3, domestic students admitted to Harvard's class of 2019 had mean and median SAT scores of 2241 and 2270, respectively, and mean and median ACT scores of 33 and 34, as well as an average converted GPA of 77 out of 80.

32. These data show that even if Harvard wanted to admit every student with elite academic credentials, it could not. Harvard admits roughly 1,800 domestic students each year, yet thousands of applicants have impeccable academic qualifications.[9] For example, based on the statistics in Exhibit 2, even if Harvard sought to admit only applicants with a perfect GPA, it would need to reject at least 6,000 such applicants *and all other domestic applicants*. Similarly, even if Harvard sought to admit only applicants with a perfect Math SAT score, it would need to reject nearly 2,000 such applicants *and all other domestic applicants*.

[9] See workpaper.

Exhibit 2

Many applicants to the class of 2019 had outstanding standardized test scores and grades



Source: Arcidiacono Data

Note: Data are from applicants to the class of 2019 using Professor Arcidiacono's expanded sample. Harvard converts applicant GPAs to a 35–80 scale.

Exhibit 3

Admitted students have strong academic credentials

	Composite SAT Score		Composite ACT Score		Converted GPA	
Class	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
1. **2014**	2227	2260	33	33	76	77
2. **2015**	2222	2260	33	33	77	77
3. **2016**	2237	2270	33	34	77	77
4. **2017**	2237	2270	33	34	77	77
5. **2018**	2243	2280	33	34	77	77
6. **2019**	2241	2270	33	34	77	78
Total	**2234**	**2270**	**33**	**34**	77	77

Source: Arcidiacono Data

Note: Data are from admitted students to the classes of 2014 – 2019 using Professor Arcidiacono's expanded sample.

3.2. Harvard seeks candidates with a wide range of skills beyond academic achievement

33. Given the extraordinary academic credentials of the Harvard applicant pool each year, the key question for any statistical analysis of the admissions process (and for assessing SFFA's analyses) is: What other characteristics does Harvard evaluate when trying to differentiate among academically capable students, and how scarce are those characteristics in the applicant pool relative to the abundance of academic credentials? In this sub-section, I summarize testimony and documents from Harvard that detail the characteristics it seeks in individual applicants, as well as the broader diversity in life experiences, perspectives, and interests it seeks for each class as a whole.

3.2.1. Harvard's whole-person evaluation relies on an "expansive view of excellence," and seeks to identify a wide variety of "distinguishing excellences"

34. The guiding principle of Harvard's admissions process, as I understand it, is to evaluate each applicant as a whole person, not just in terms of her academic qualifications but in terms of all other attributes. Documents from Harvard indicate that a central goal of Harvard's whole-person evaluation process is an assessment of each applicant's potential to contribute in various ways to Harvard's educational environment and campus community. This process requires a careful assessment of the aspects of each applicant that distinguish her from other applicants, as well as an assessment of the context in which the applicant's achievements occurred, such as the availability of opportunities to the applicant and the difficulty of the challenges the applicant has faced. Importantly, documents indicate that academic strength on its own is generally not sufficient to distinguish an applicant. In fact, Harvard's 2014 – 2015 Interviewer Handbook ("Interviewer Handbook") notes that **Redacted** [10]

35. The Interviewer Handbook summarizes what Harvard refers to as its "Search for Distinguishing Excellences" as follows:

Redacted

[10] Interviewer Handbook, 2014 – 2015, HARV00001392 – 1438 ("Interviewer Handbook") at HARV00001401. Other documents from Harvard support this account of the admissions process. For example, in a presentation given to guidance counselors at schools in the Sarasota, Florida area, Harvard admissions officer Kanoe Williams explained that test scores are just a "small piece" of Harvard's whole-person evaluation; that, "in general, we can tell pretty quickly if a student will be an academic fit for our school"; and that "the lengthier part of the conversation typically focuses on intangibles, the qualitative pieces" (Sarasota Presentation, "KLW - Sarasota Presentation," HARV00013561 – 65 at HARV00013563 – 64).

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36. The Interviewer Handbook then goes on to list a variety of examples of "distinguishing excellences" that admissions officers look for when reviewing application files:

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[11] Interviewer Handbook at HARV00001400 – 01.

[12] Deposition testimony indicates that the personal essay is also a key factor in evaluating personal qualities. See, for example, Deposition of Roger Banks, May 4, 2017 ("Banks Deposition"), pp. 79–80 ("Q. And for each of those categories, can you tell me how they were assigned a numerical score?...[A] Extracurricularly, quality of achievement, strength of performance in any particular domain, personal qualities, some grasp of the candidate's personality, interest in other people, cooperation with others, a sense of responsibility as gleaned from teacher recommendations, personal interview, personal essay, et cetera. Q. Okay. So for the last category, the—the main inputs you would look at were recommendations, interview, and anything else? A. The candidate's essay."); Deposition of Brock Walsh, June 28, 2017 ("Walsh Deposition"), p. 60 ("Q How would you calculate that score?…[A.] I would like to take into consideration whatever relevant information I had were that his essay, her essay, her interview, and the opinions about that applicant as expressed by others."); Deposition of Tia Ray, June 7, 2017 ("Ray Deposition"), pp. 21–22 ("Q. What are the materials that you use—materials or considerations that go into determining this person's score?…A. For example, content in recommendation letters, personal essays.").

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3.2.2. Harvard evaluates applicants' distinguishing excellences within the context of their full life experience, including their high school, community, family, and other factors

37. Harvard's assessment of each applicant's overall qualifications and distinguishing excellences takes into account the full context of the applicant's life experience. My understanding is that Harvard seeks to understand the opportunities and challenges each applicant has faced so that it can better evaluate each applicant's achievements and potential to contribute to Harvard. For example, William Fitzsimmons, Harvard's Dean of Admissions and Financial Aid, testified that the context of each *high school* is particularly important when evaluating the qualifications of any given applicant:

> Given the fact that we want to understand as completely as possible what the … applicant has accomplished both in school, out of school, you know, throughout his or her life, getting to know the school, the opportunities within the school, academically, extracurricularly, and in other ways, what they might learn from fellow students, all the usual things that you might look for in a college that would be of interest. And also is interesting for the—helpful for readers to understand which courses might be tougher than others, things of that sort, the full context.[14]

38. Marlyn McGrath, Director of Admissions, also testified that the Admission Committee's assessment of the context of each applicant's family life and community is crucial to the evaluation of her achievements:

> The most important thing to say is that when an applicant has applied, each applicant is really considered as an individual, including—whose candidacy will always include, generally include, many factors, family

[13] Interviewer Handbook at HARV00001401 – 02.

[14] Deposition of William Fitzsimmons, August 3, 2017 ("Fitzsimmons Deposition"), pp. 233–234.

> background, which will include whatever we know of race, whatever else we know about family circumstances and education, whatever we can know about the nature of the school and the kind of community the student grew up in. Those context features, those features of the student's setting are always important to us in imagining how well he's achieved in the circumstances that he started with to us as a candidate.[15]

3.2.3. Documents from Harvard identify specific examples of qualifications that help applicants distinguish themselves from others

39. To help train admissions officers and alumni interviewers to identify the types of "distinguishing excellences" detailed above, as well as how to evaluate each candidate's accomplishments in context, Harvard maintains a Casebook and Casebook Discussion Guide that highlight examples based on actual application files.[16] The discussion guide aims to highlight **Redacted** **Redacted**

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40. Below are a variety of examples from applications in the Casebook that illustrate the wide variety of factors Harvard considers in order to distinguish among the many academically strong candidates in its pool. These factors include, for example, personal qualities like intellectual arrogance or social charm, economic resources and family hardship, personal essays and interviews, artistic qualities, maturity and ability to balance multiple commitments, and the degree of parental involvement:

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[15] Deposition of Marlyn McGrath, Volume I, June 18, 2015 ("McGrath Deposition 2015"), pp. 231–232.

[16] 2012 Casebook, HARV00000212 – 321 ("Casebook"); Discussion Guide to the 2012 Casebook, HARV00018164 – 176 ("Casebook Discussion Guide").

[17] Casebook Discussion Guide at HARV00018165.

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3.2.4. Harvard seeks diversity of life experience and perspectives for each class on numerous dimensions

41. As noted above, my understanding is that Harvard seeks to admit not just a set of individuals with distinguishing excellences, but also a class that includes individuals with a wide range of life experiences and perspectives.

42. For example, the 2016 Report of the Committee to Study the Importance of Student Body Diversity, chaired by Dean of Harvard College Rakesh Khurana ("Khurana Report"), states:

> The mission of Harvard College is to educate the citizenry and citizen leaders for our society. We take this mission very seriously and firmly believe it is accomplished through the transformative power of a liberal arts and sciences education. That transformation begins in the classroom with exposure to new ideas, new ways of understanding and new ways of knowing. It is further fostered through a diverse residential environment where our students live with peers who are studying different subjects, who come from different walks of life, and have different identities. This exposure to difference not only deepens a student's intellectual transformation, but also creates the conditions for a social transformation as students begin to question who they are and how they relate to others.[19]

43. One form of diversity that Harvard seeks is racial diversity. For example, President Faust testified: "It's important that we have a class that represents diversity along a number of dimensions, and race is one of those dimensions. Economic status is another. Artistic ability is another. Life experience is another. Interest in a variety of fields that we represent is another."[20]

44. Dean Fitzsimmons described how the Admissions Committee considers an applicant's self-reported race as one among many factors as it seeks to admit a diverse class:

[18] Casebook Discussion Guide at HARV00018165 – 169, HARV00018174 – 175.

[19] "Report of the Committee to Study the Importance of Student Body Diversity," HARV00008048 – 69 ("Khurana Report") at HARV00008048.

[20] Deposition of Catherine Drew Gilpin Faust, March 10, 2017 ("Faust Deposition"), p. 196.

> We know that race is one factor among many as we review each application…There are students who might write an essay on how formative and important race was. There are students who might not present themselves in such a way. But as one were to look at the application in its entirety, you could come to the conclusion that race certainly may have been a factor in their person's life and may help that person be a better educator of others during college and beyond. Each application is different, one from the next.[21]

3.3. Harvard's decision process is labor-intensive and seeks to understand the full context of each applicant's high school achievements

45. Based on my review of deposition testimony and documents produced in this matter, I understand that, to implement its whole-person assessment of each applicant, Harvard has implemented a multi-stage decision process with input from a large team of admissions officers.[22] Dean Fitzsimmons has described this as a "rigorous comparative process."[23]

46. The Admissions Committee is divided by geographic region into twenty subcommittees, known as dockets.[24] Each subcommittee normally includes four to five members and a chairperson, who are collectively responsible for the initial evaluation of all candidates from the geographic area.[25] Each member of a subcommittee is responsible for performing the initial read of all applications from a set of high schools on the docket. My understanding is that admissions officers often sit on multiple subcommittees. The admissions officer who conducts the first read of a given application (the "first

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[21] Fitzsimmons Deposition, pp. 87–88.

[22] Applicants have the option to apply "Early Action" to Harvard. Early Action applications are due in November, and if an applicant applies early to Harvard, he may not apply to any other private university's Early Action or Early Decision program. Offers of admission to Early Action candidates are announced in December, and are non-binding (that is, an applicant offered Early Action admission may still apply to other universities in the Regular Decision cycle). Early Action applicants who are not accepted in December are either denied admission or "deferred" – that is, shifted into the Regular Decision pool and reconsidered during the Regular Decision admissions cycle. I understand that the subcommittee and full committee processes for Early Action applicants are primarily the same as described above for Regular Decision, but with far fewer applications (Harvard College, "Restrictive Early Action," available at https://college.harvard.edu/admissions/apply/application-timeline/restrictive-early-action, accessed August 14, 2017).

[23] William Fitzsimmons, "Guidance Office: Answers From Harvard's Dean, Part 1," New York Times, September 10, 2009, available at https://thechoice.blogs.nytimes.com/2009/09/10/harvarddean-part1/, accessed November 10, 2017.

[24] Two of the twenty dockets (U and V) are comprised entirely of applicants from international high schools.

[25] William Fitzsimmons, "Guidance Office: Answers From Harvard's Dean, Part 1," New York Times, September 10, 2009, available at https://thechoice.blogs.nytimes.com/2009/09/10/harvarddean-part1/, accessed November 10, 2017.

reader") can choose to pass the application on to the subcommittee chair for review if the first reader believes that the application merits further consideration.[26]

47. I understand that admissions officers focus on specific high schools in their geographic regions, gain detailed knowledge of those high schools, and rely on that knowledge when evaluating applications.[27] In particular, I understand that admissions officers rely on such knowledge to better evaluate candidates within the context of the academic and non-academic opportunities and challenges that they have encountered at their particular high schools.[28] As I discuss below, accounting for high school context in a statistical model of the admissions process is critical because it is one of the important ways in which admissions officers distinguish among candidates.

48. Once all applications from a particular docket have been reviewed, the subcommittee for that docket meets to discuss the applications. My understanding is that during this process, the first reader summarizes the strength of the applications he or she has read. Subcommittee members discuss applications, and then vote on each application to recommend an action to the full Committee. The degree of support expressed for applicants is noted to allow for comparisons with applicants from other subcommittees.[29] The full Admissions Committee then meets to discuss the candidates recommended by each subcommittee. For Regular Decision applicants, full committee meetings take place over the course of approximately two weeks during March.[30]

49. My understanding is that during the full committee process, the first reader, or area

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[26] Deposition of Caroline A. Weaver, Volume II, March 6, 2017 ("Weaver Deposition, Volume II"), p. 221 ("If I read an application and thought that it was a strong application, I would pass it to the chair of the docket.").

[27] Fitzsimmons Deposition, p. 233 ("The beginning piece of the evaluation, you know, would be as, for example, if I covered Chicago, that I would typically be the first reader of an application from that area. Q. And, in fact, the readers within a particular docket are divided up by high schools within the docket? A. Yes. Q. So the same reader is supposed to read all the applications from a particular school? A. Yes. Q. Is that done so that there's better understanding of the way the school works and the level of classes and information that is going to apply to all applicants? … A. That's certainly one of the reasons.").

[28] Fitzsimmons Deposition, pp. 233–234 ("Q. Is that done so that there's better understanding of the way the school works and the level of classes and information that is going to apply to all applicants? … A. That's certainly one of the reasons. There are others. Q. What are the others? A. Given the fact that we want to understand as completely as possible what the applica—what the applicant has accomplished both in school, out of school, you know, throughout his or her life, getting to know the school, the opportunities within the school, academically, extracurricularly, and in other ways, what they might learn from fellow students, all the usual things that you might look for in a college that would be of interest. And also is interesting for the—helpful for readers to understand which courses might be tougher than others, things of that sort, the full context.").

[29] William Fitzsimmons, "Guidance Office: Answers From Harvard's Dean, Part 1," New York Times, September 10, 2009, available at https://thechoice.blogs.nytimes.com/2009/09/10/harvarddean-part1/, accessed November 10, 2017.

[30] Admissions Calendar 2013 – 2014, HARV00031933.

person, for an application generally presents the applicant's file to the full Committee, and may choose to project portions of the application on a screen during the discussion so that the Committee can review important components of the application.[31] For example, deposition testimony indicates that the admissions officer presenting the case might use excerpts of visual art or music submissions or academic papers to highlight an applicant's skills,[32] and that discussions in subcommittee or in full Committee on a single applicant may range in length up to a half hour or more.[33] The full Committee compares all candidates across all subcommittees.[34]

50. According to Dean Fitzsimmons, "[t]his rigorous comparative process strives to be deliberate, meticulous, and fair. It is labor intensive, but it permits extraordinary flexibility and the possibility of changing decisions virtually until the day the Admissions Committee mails them."[35]

3.4. Harvard's ratings reflect important and otherwise unobservable information about the academic and non-academic qualifications of applicants

51. To help quantify and formalize the evaluation of each applicant by the Admissions Committee, Harvard employs a numeric rating system. Each admissions officer who reviews an application rates the applicant on four key dimensions: academic, extracurricular, athletic, and

[31] Deposition of Chris Looby, June 30, 2017 ("Looby Deposition"), pp. 33–34 ("Q. Do you ever put a summary sheet on a projection screen? A. Yes, we do.").

[32] Deposition of Roger Banks, May 4, 2017 ("Banks Deposition"), pp. 197–198 ("A. The area person would begin with an overall summary of the case, its significant features, academically and extracurricularly, arguments to admit, and proceed to point the committee toward evidence to support those arguments. Q. Would the members have any other materials that they're looking at during that conversation, or is it just what's presented here? A. It would be what's presented here in addition to supplemental information, music tapes, visual art supplements, academic papers, things of that kind.").

[33] Fitzsimmons Deposition, p. 157 ("But, again, there's no way to, you know, when 40 people are listening in some cases for half an hour or more to a single application and discussing that application, exactly why they would choose to admit that applicant—just impossible to quantify that kind of thing.").

[34] Fitzsimmons Deposition, pp. 297–298 ("And so, in the end, all of those students are—have to be compared against all of the other people from all the other dockets, and lots of times there's new information available. You know, there could be any number of new pieces of information, new interview or whatever, and that might make for a different case. So every one ultimately gets compared to everyone else in the same process that I have mentioned earlier today, where you would literally—if you were, say, the area person for a candidate from a school, there would be a docket that people could look at but then all the information about that applicant would have to go up on the screen and you would have to make your argument in front of the full committee.").

[35] William Fitzsimmons, "Guidance Office: Answers From Harvard's Dean, Part 1," New York Times, September 10, 2009, available at https://thechoice.blogs.nytimes.com/2009/09/10/harvarddean-part1/, accessed November 10, 2017.

personal.[36] These are referred to as "profile ratings." Admissions officers also assign numerical ratings to the applicant's "school support"—that is, recommendation letters submitted by high school teachers and guidance counselors.[37] Applicants who receive alumni interviews also receive ratings from their interviewers, and some applicants may receive additional ratings from interviews by admissions staff.[38] Applicants who submit recordings of musical performances may also receive a numerical rating assigned by a member of Harvard's music faculty.[39]

52. **Redacted**

53. Admissions officers and alumni interviewers also assign applicants an overall rating.[42] Deposition testimony indicates that the overall rating (a) takes into account the profile ratings but is not a formulaic summation or average of those ratings, and (b) can reflect other aspects of an application that the reviewer considered but that are not captured in the profile ratings (including race).[43] I understand that the numerical ratings in the database may not include certain other

[36] These ratings are generally assigned early in the application-reading process, so they do not always reflect information—such as a faculty evaluation of an applicant's academic work, or an alumni interview—that may arrive later on (2018 Reading Procedures at HARV00015414 – 15, HARV00015423 – 24).

[37] 2018 Reading Procedures at HARV00015416.

[38] Interviewer Handbook at HARV00001418; Interview Information Sheet Class of 2017, HARV00000008 – 09 at HARV00000009; Deposition of Sarah Donahue, June 6, 2017 ("Donahue Deposition"), pp. 193–195 ("Q. … Do the alumni interviewers themselves assign scores for the applicants which they interview? A. Yes. Q. And is that also on the four-point scale or the four-number scale? A. Yes. … Q. When there are staff interviews, does the staff assign numbers in the same way that the alumni interviewers do? … A. They are the same two categories.").

[39] 2018 Reading Procedures at HARV00015424.

[40] 2018 Reading Procedures at HARV00015414 – 16.

[41] 2018 Reading Procedures at HARV00015415 ("Extracurricular, Community Employment, Family Commitments … 5. Substantial activity outside of conventional EC participation such as family commitments or term-time work…").

[42] 2018 Reading Procedures at HARV00015414; Interviewer Handbook at HARV00001429; Interview Information Sheet Class of 2017, HARV00000008 – 09.

[43] Fitzsimmons Deposition, pp. 249–250; McGrath Deposition 2015, pp. 172–173; Deposition of Lucerito Ortiz, June 14, 2017 ("Ortiz Deposition"), pp. 28–29; Deposition of Kaitlin Howrigan, June 20, 2017 ("Howrigan Deposition"), pp. 32–33; Deposition of Brock Walsh, June 28, 2017 ("Walsh Deposition"), pp. 61, 66–67. For testimony addressing how race may be taken into account as one of many factors considered when assigning an overall rating, see Ray Deposition, pp. 27–28 ("Q. Is race taken into account when you give a student an overall rating? A. It depends. … Q. How so? … A. On the individual case and the individual admissions officer," and "Q. Why is it different—why do you take race into account in the overall rating but in none of the other ratings? ... A. It depends on the individual case. And we may take it into

assessments that the Admissions Committee may receive during the course of the admissions process—for example, evaluations that Harvard faculty members may provide of academic work that an applicant has submitted.[44]

54. Each rating is designed to capture numerous characteristics of the applicant that Harvard values, many of which extend beyond easily quantifiable measures like test scores. For example, documents and testimony in this case reveal that the academic rating can reflect not only the applicant's grades and test scores but also the admissions officer's knowledge of the applicant's high school (and thus ability to place in context the applicant's academic accomplishments, given the applicant's opportunities), as well as the officer's knowledge of the strength of the candidate's high school curriculum, appraisals of the candidate's academic work by Harvard faculty (to the extent such appraisals are received before the academic rating is assigned), and the candidate's receipt of academic honors or awards.[45] It may also reflect the applicant's writing skills.[46] The extracurricular rating, likewise, reflects not only the number of extracurricular activities in which an applicant has participated and the number of hours the applicant has devoted to those activities, but also the nature of the applicant's activities, whether the applicant has held leadership roles, and whether the activities are highly selective.[47]

55. A written set of "Reading Procedures" summarizes the protocols that admission officers are to follow when reviewing an application and sets forth "coding guidelines" that guide how admissions officers assign profile ratings. The coding guidelines provide standards for when to assign each rating. For example, a "1" academic rating means: **Redacted**

[48] Only about 100 applicants per year receive a 1 academic rating, despite the large numbers of applicants with extraordinary GPA and SAT/ACT scores, reflecting the critical importance of information beyond grades and standardized test scores that the readers incorporate

account in that overall rating to reflect the strength of the case and to provide a slight tip for some students."); Howrigan Deposition, pp. 35–36 ("Q. So is your answer yes, as long as you knew the student's race, you would take it into account [in assigning the overall rating]? … A. If the student opted to share that information on their application, that was something that was taken into account, with hundreds of other factors that were being taken into account."); Weaver Deposition, Volume II, p. 194 ("Q. How does the applicant's race factor into the overall score? … A. I wouldn't say that it factors in directly. Q. But it does factor in indirectly in instances? … A. An applicant's race becomes important in cases where the applicant makes that an important part of their folder, if it's an important part of their identity and the way they express themselves in their application.").

[44] Harvard Memo, "RE: Faculty Readings," November 9, 2013, HARV00009879 – 80.

[45] 2018 Reading Procedures at HARV00015414; Fitzsimmons Deposition, pp. 240–241; McGrath Deposition 2015, pp. 161–162, 166, 168–169; Banks Deposition, p. 80.

[46] Banks Deposition, p. 80 ("A. For academics, … some sense of the student's writing skills.").

[47] 2018 Reading Procedures at HARV00015415; McGrath Deposition 2015, pp. 163, 169–171; Donahue Deposition, p. 160; Ray Deposition, p. 19.

[48] 2018 Reading Procedures at HARV00015414.

into the ratings.

56. The importance of the ratings in the decision process can be seen in their correlation with admissions decisions. Exhibit 4 shows how admission rates vary for applicants with different combinations of profile ratings. For example, it shows that candidates who are exceptionally strong in a single dimension (reflected by an academic, athletic, extracurricular, or personal rating of 1 and no other ratings of 1) and candidates who are multi-dimensional (i.e., have at least three profile ratings of 2) are admitted to Harvard at rates much higher than those of candidates with no ratings of 1 or 2. Applicants with an academic rating of 1 and no other ratings of 1 are admitted 68% of the time. Applicants with an extracurricular, personal, or athletic rating of 1 and no other ratings of 1 also have high admissions rates (48%, 66%, and 88% respectively). Applicants with a rating of 2 on all four profile ratings are admitted 68% of the time. By contrast, applicants whose four profile ratings are all 3 or worse have almost no chance of admission to Harvard (0.1%).

Exhibit 4

Specific combinations of Harvard's four profile ratings have a large effect on the admission rate

Ratings Combination	Number of Applicants	Admission Rate
Candidates who Excel on One Dimension		
1. **Academic rating of 1, no other 1s**	663	68%
2. **Extracurricular rating of 1, no other 1s**	453	48%
3. **Personal rating of 1, no other 1s**	41	66%
4. **Athletic rating of 1, no other 1s**	1,340	88%
Multi-Dimensional Candidates		
5. **Three ratings of 2, one rating of 3 or 4**	9,266	43%
6. **Four ratings of 2**	622	68%
Weaker Candidates		
7. **No ratings of 1 or 2**	55,981	0.1%

Source: Arcidiacono Data

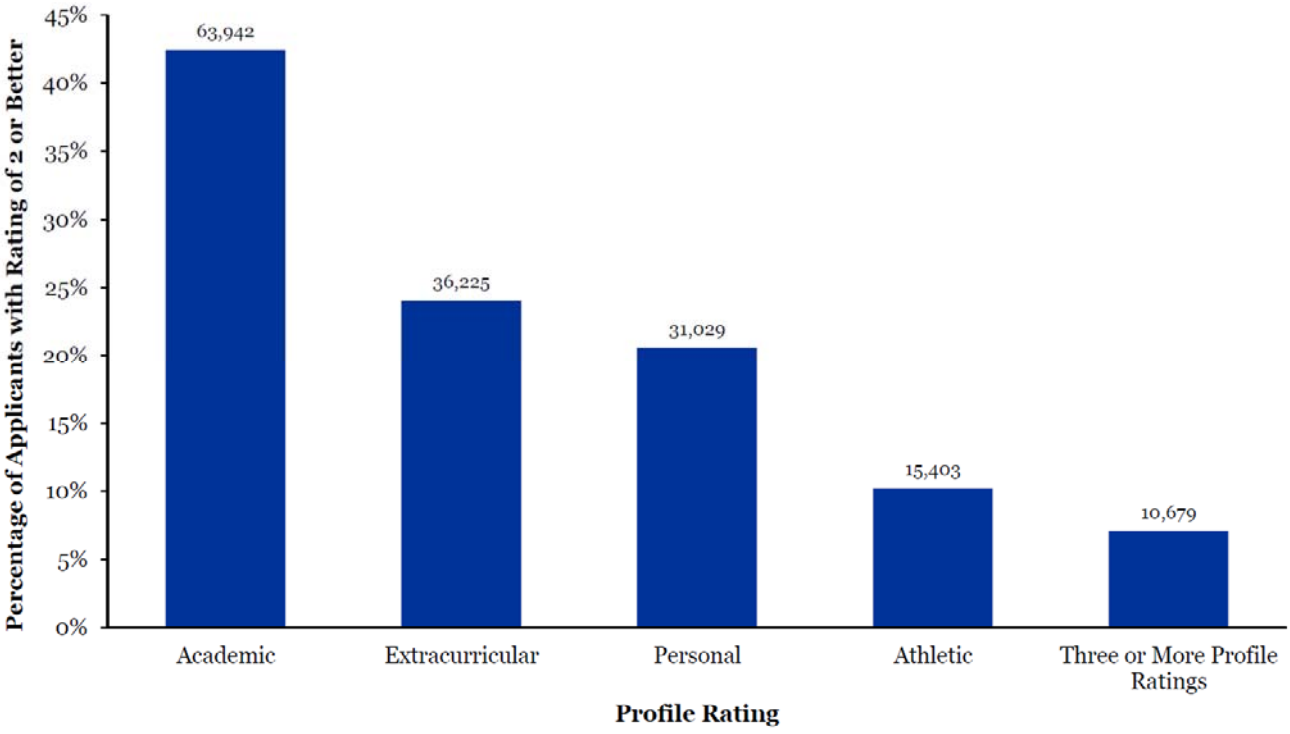
Note: Data are from applicants to the classes of 2014 – 2019 using Professor Arcidiacono's expanded sample.

57. The ratings also indicate that applicants who are highly rated on non-academic dimensions are much scarcer than applicants with a high academic rating. Exhibit 5 shows that about 42% of applicants have an academic rating of 1 or 2, while fewer than 25% of applicants receive a 1 or 2 on each of the other three profile ratings. Applicants with a rating of 2 or better on at least three dimensions are even rarer—just 7% of the applicant pool. These data indicate that high ratings on

non-academic dimensions (and particularly on multiple non-academic dimensions) distinguish applicants in the pool much more effectively than a high academic rating.

Exhibit 5

Strong academic ratings are more common than strong extracurricular, athletic, and personal ratings



Source: Arcidiacono Data

Note: Data are from applicants to the classes of 2014 – 2019 using Professor Arcidiacono's expanded sample.

58. Another way to see the importance of non-academic dimensions relative to academic dimensions of excellence is to examine how important each element is in explaining which applicants are admitted. As discussed more fully below, a statistic called the Pseudo R-Squared (on which Prof. Arcidiacono relies frequently in his analysis) captures how well a variable or set of variables can explain outcomes—in this case, admissions decisions. The statistic takes on values from zero to one; the closer it is to zero for a given model, the less information the variables in that model provide about admissions decisions, while a value closer to one means the model explains a higher proportion of the variability in the actual decisions. In Prof. Arcidiacono's expanded sample, the Pseudo R-Squared of a model that includes only the academic rating as a control variable is 0.09, while the Pseudo R-Squared of models that include each of the three non-academic ratings as the sole control variables are 0.20 (personal), 0.09 (extracurricular), and 0.08 (athletic), and the Pseudo R-Squared for

a model that includes all three non-academic ratings as control variables is 0.32.[49] In non-technical terms, this means that non-academic factors (taken together) explain more than three times as much of the variation in admissions decisions as the academic rating does. That should not be surprising, since exceptional non-academic qualities are less common in the applicant pool than exceptional academic qualities and are thus more likely to distinguish applicants from one another.

59. Consistent with the discussion above, Exhibit 6 shows that only 12% of admitted students are "one-dimensional stars" with a rating of 1 on one dimension but fewer than three ratings of 2 or better, while 46% are multi-dimensional applicants with three or four ratings of 2 or better, and 31% have two ratings of 2 and two ratings of 3. These statistics are yet another way to show the value that Harvard places on applicants who distinguish themselves on multiple dimensions.

Exhibit 6

The vast majority of admitted students excel in multiple dimensions

	Ratings Combination	Number of Admitted Students	Share of Admitted Students
1.	**Multi-dimensional excellent candidates: three or more ratings of 2 or better**	5,103	46%
2.	**Multi-dimensional solid candidates: two ratings of 2, two ratings of 3**	3,480	31%
3.	**Candidates who excel on one dimension: one rating of 1, fewer than three ratings of 2 or better**	1,333	12%

Source: Arcidiacono Data

Note: Data are from applicants to the classes of 2014 – 2019 using Professor Arcidiacono's expanded sample. Category 2 also includes five applicants who received two ratings of 1 and two ratings of 3.

60. One final point about the ratings warrants mention. Prof. Arcidiacono argues that the athletic rating "has little impact on admissions outside of recruited athletes,"[50] and that "once athletes are taken out, the relationship between the athletic rating and admissions is weak."[51] These assertions directly contradict both testimony and documents from Harvard, as well as the admissions data.

[49] See workpaper.

[50] Arcidiacono Report, p. 5, footnote 5.

[51] Arcidiacono Report, p. 24, footnote 31.

61. For example, as noted above, the Interviewer Handbook explicitly notes that athletic ability can be a "distinguishing excellence" and is **Redacted**

[52] This "tip" is not limited to recruited varsity athletes; it also reflects the value Harvard places on recreational athletics and an applicant's potential contribution to life in Harvard's residential Houses. For example, the Interviewer Handbook notes: **Redacted**

[53] The Reading Procedures also note **Redacted**

62. Harvard's admissions data confirm the importance of the athletic rating. For example, applicants with an athletic rating of 2 have an admission rate of 12%. That is substantially higher than the overall admission rate of approximately 7%, and is the same as the admission rate of applicants with an academic rating of 2. Further, as shown above, receiving a rating of 2 on all four profile ratings is associated with an admission rate of 68%, while receiving a rating of 2 on the three non-athletic ratings and a rating of 3 or worse on the athletic rating is associated with an admission rate of only 48%. This contrast provides further evidence of the incremental importance of an athletic rating of 2.[55]

3.5. Prof. Arcidiacono's statistical model fails to account for numerous dimensions of Harvard's admissions process

63. Prof. Arcidiacono's analysis clearly fails to reflect the complexity of the admissions process described above.

64. First, although Harvard values academic achievements, academic qualifications are only one factor in the evaluation of each candidate, and applicants with exceptional academic records are abundant in the Harvard applicant pool. Harvard's whole-person evaluation extends beyond test scores, GPA, and other measures of prior academic achievement.[56] Yet Prof. Arcidiacono focuses overwhelmingly on the relative academic strength of Asian-American applicants. For example, in

[52] Interviewer Handbook at HARV00001401.

[53] Interviewer Handbook at HARV00001402.

[54] 2018 Reading Procedures at HARV00015415.

[55] See workpaper.

[56] Sarasota Presentation, "KLW - Sarasota Presentation," HARV00013561 – 65 at HARV00013563.

four of his six regression specifications, Prof. Arcidiacono does not include controls for the three non-academic ratings (extracurricular, personal, and athletic). Such models are incapable of accounting for the admissions process detailed above, and shed no useful light on the issues in this case.

65. Second, as I detail in the next section, it is difficult to quantify and include in a statistical model many of the non-academic and contextual factors that Harvard's admissions process values. That is particularly important for assessing racial disparities in admission because, as I show in the next section, there are significant racial differences in the non-academic and contextual factors that are measured in Harvard's admissions database and that Prof. Arcidiacono chooses not to include in his model. That suggests there may well also be racial differences in the many other non-academic factors (like the personal essay) that are *not* observable in the database and that are important to the admissions process given the large pool of applicants with extraordinary academic achievements.

4. ACCOUNTING FOR NON-ACADEMIC AND CONTEXTUAL FACTORS IS CRITICAL IN MODELING HARVARD'S ADMISSIONS PROCESS

66. Before turning to my formal statistical analyses in Sections 5, 6, and 7, in this section I discuss several facts that Prof. Arcidiacono has overlooked (or misunderstood), that provide important context for the more technical analysis that follows in the remainder of this report, and that illustrate the flaws in Prof. Arcidiacono's arguments.

67. I start by examining the differences in admission rates between Asian-American and White applicants. One of SFFA's central claims in this matter is that Asian-American applicants are admitted at a lower rate than White applicants. As I show below, however, that is not true if one focuses on applicants who are neither lineage applicants, nor recruited athletes, nor children of Harvard faculty and staff, nor included on the Dean's and Director's interest lists—all categories of applicants that Prof. Arcidiacono believes should be removed from an analysis of bias. Fully 95% of applicants fall outside those categories.[57] And among that 95% of applicants, Asian-American applicants are admitted at slightly *higher* rates than White applicants.

68. I then explain why the data do not support one of the central assumptions of Prof. Arcidiacono's analysis—that Asian-American applicants are stronger on all dimensions of quality, including non-academic characteristics. As I detail below, White applicants are stronger on average than Asian-American applicants across the three non-academic profile ratings combined, and are stronger (in aggregate) across all of the non-academic variables that can be observed in the database and that are included in Prof. Arcidiacono's model. As noted earlier, the observable measures of non-academic achievement are also limited: it is clear from the documents and testimony in this case that Harvard is using other information such as recommendation letters and the applicants' personal essays to form its assessments of each candidate's non-academic strengths. This information is "missing data" that cannot be observed in the admissions database. If the racial gaps in these missing data are similar to the racial gaps in the observed measures of non-academic achievement, then Prof. Arcidiacono's model is biased *in favor of* finding an adverse effect of Asian-American ethnicity on applicants' probability of admission, since it omits variables that, if included as controls, would decrease the size of (or eliminate entirely) the estimated negative effect of Asian-American ethnicity.

69. Finally, Prof. Arcidiacono's model includes very little information to account for the overall context of each candidate's application (such as the quality of the applicant's high school, the socioeconomic characteristics of the applicant's high school and neighborhood, and the applicant's family background), even though Prof. Arcidiacono had access to data that shed light on all those factors. Using these data, I highlight a variety of average differences between White and Asian-

[57] See workpaper.

American applicants that I understand to be relevant to Harvard's whole-person analysis. For example, White and Asian-American applicants tend to come from different sets of high schools and different parts of the country, have parents with different occupational backgrounds, and have different intended careers. All of these factors provide important context for reviewing applications.

4.1. There is no statistically significant difference in admission rates for the vast majority of Asian-American and White applicants

70. SFFA's claim of bias relies heavily on the premise that Asian-American applicants are admitted at lower rates than White applicants despite having stronger qualifications. But as Prof. Arcidiacono acknowledges in his report, when exploring whether there is bias against Asian-American applicants, it is important to account for the fact that Harvard's admissions process gives special consideration (independent of race) to children of Harvard or Radcliffe alumnae or alumni (referred to as "lineage applicants," and which Prof. Arcidiacono refers to as "legacy applicants"), applicants recruited to play a varsity sport at Harvard, and children of Harvard faculty or staff members. The Dean and Director of Admissions also maintain "interest lists" of applicants; I understand that there are no particular criteria for inclusion on those lists but that they might include, for example, applicants that the Dean or Director have encountered at recruiting events, as well as applicants related to donors to Harvard or lineage applicants.[58] Indeed, Prof. Arcidiacono removes applicants in those categories from what he calls his "baseline" sample, before exploring the question of bias.[59]

71. Exhibit 7 shows the admission rates by race, once applicants in the categories noted above are excluded from the sample. It shows that Asian-American applicants are admitted at a slightly *higher* rate than White applicants (though the difference is not statistically significant). Although the numbers in Exhibit 7 do not settle the question of whether there is bias against Asian-American applicants (because they do not account for the full set of characteristics of each applicant), the fact that the difference in admissions rates disappears by controlling for just these factors raises serious questions about SFFA's allegations of bias. The remainder of this section explores a variety of other important factors that differ between White and Asian-American applicants and that, once accounted for, eliminate the alleged disparity in admission rates.

[58] Fitzsimmons Deposition at pp. 264–267, 278.

[59] Prof. Arcidiacono also removes from his baseline sample applicants who apply during the Early Action cycle (Arcidiacono Report, p. 2). I do not follow that approach here. I understand that the process for evaluating Early Action applications is the same as that for evaluating Regular Decision applications except that Early Action applications are evaluated earlier and have the potential to be deferred to the Regular Decision pool.

Exhibit 7

Admission rates for applicants who are not lineage applicants, athletic recruits, children of Harvard faculty or staff, or on Dean's or Director's Interest List

Class	White Admission Rate	Asian-American Admission Rate	Difference (Percentage Points)
1. **2014**	6.46%	6.30%	-0.15
2. **2015**	5.28%	5.07%	-0.21
3. **2016**	5.07%	5.48%	0.41
4. **2017**	4.50%	5.04%	0.54
5. **2018**	4.24%	4.40%	0.16
6. **2019**	3.91%	4.77%	0.86
Total	4.91%	5.15%	0.24

Source: Arcidiacono Data

Note: Data are from applicants to the classes of 2014 – 2019 in Professor Arcidiacono's baseline sample with Early Action applicants.

4.2. White applicants have relatively stronger qualifications on non-academic dimensions

72. A central assumption in Prof. Arcidiacono's analysis is that, because Asian-American applicants are stronger on academic dimensions, they are also stronger on non-academic dimensions—including those dimensions not accounted for by his model.[60] This assumption leads Prof. Arcidiacono to focus much of his analysis on academic qualifications, and to conclude that any difference in admission rates not accounted for by his model must be caused by "bias" against Asian-American applicants. As I show in this sub-section, however, a proper interpretation of the available data indicates that Prof. Arcidiacono's assumption is incorrect. White applicants are in fact stronger, on average, on non-academic factors that Harvard values.

73. Exhibit 8 shows that Asian-American applicants tend to have higher academic ratings and slightly higher extracurricular ratings than White applicants, while White applicants tend to have higher personal and athletic ratings[61] and are more likely to be multi-dimensional (i.e., more likely to have a rating of 2 or better on at least three of the four profile ratings). Importantly, the average

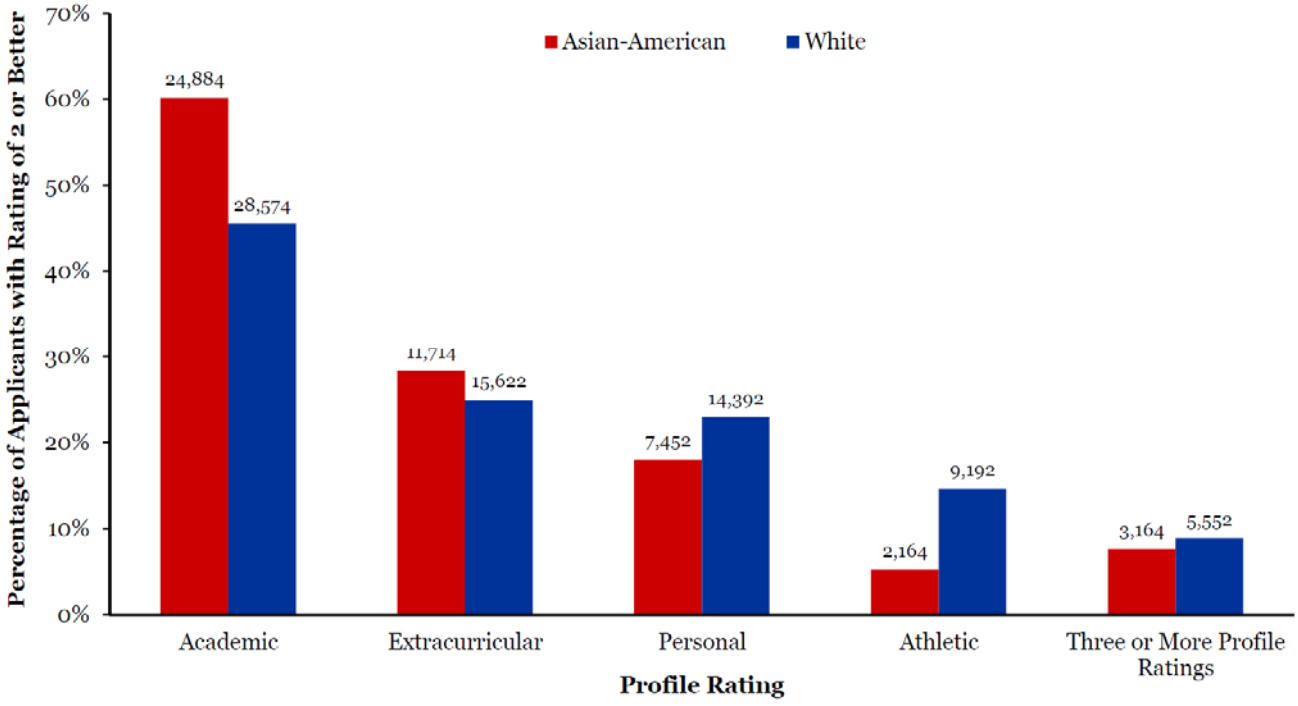
[60] Throughout his report, Prof. Arcidiacono presents a variety of analyses that show how non-academic ratings correlate with Harvard's academic index. He does not, however, directly examine whether Asian-American applicants are stronger than White applicants collectively across all non-academic factors in his model. My analysis in this section explores that question.

[61] As I discuss in Section 5 below, even if one grants Prof. Arcidiacono's assumption that personal ratings are biased against Asian-American applicants, his own analysis shows that White applicants still have higher personal ratings even after statistically eliminating the supposed bias.

difference between Asian-American and White applicants on extracurricular ratings (the one non-academic rating on which Asian-American applicants perform better than White applicants) is smaller in magnitude than the average differences in athletic and personal ratings (on which White applicants perform better than Asian-American applicants).

Exhibit 8

White and Asian-American applicants excel in different dimensions: percentage of applicants with ratings of 2 or better



Source: Arcidiacono Data

Note: Data are from applicants to the classes of 2014 – 2019 using Professor Arcidiacono's expanded sample. Ratings of 2- and above are classified as "2 or Better" in this analysis. +/- rating designations are available in the data beginning with the class of 2019.

74. Exhibit 9 presents another way to measure the difference between Asian-American applicants and White applicants on non-academic characteristics—one that accounts for the *collective* strength of each applicant across all three non-academic profile ratings. It shows the proportion of applicants with a given academic rating whose cumulative non-academic rating—that is, the sum of the extracurricular, athletic, and personal ratings—is seven or less.[62] A cumulative non-academic

[62] Applicants with athletic or extracurricular ratings of 5 and 6 are excluded from this analysis because those ratings indicate that there were special circumstances that caused the applicant to have fewer athletic or extracurricular

rating of seven or less indicates a candidate who is very strong across all three non-academic dimensions. The cutoff of seven is also highly informative about admissions probabilities: applicants whose non-academic ratings add up to seven or less have a 38% admission rate, while those with a higher sum have only a 4% chance of admission.[63]

75. Exhibit 9 shows that, for a given academic rating, White applicants are much more likely to have strong non-academic ratings than Asian-American applicants. For example, for applicants with an academic rating of 1, 25% of White applicants have very strong non-academic ratings, compared to only 16% of Asian-American applicants (roughly one-third fewer). Similarly, among the large group of applicants with an academic rating of 2 (representing nearly half of Asian-American and White applicants), 14% of White applicants, but only 8% of Asian-American applicants, have very strong non-academic ratings. This gap in non-academic achievement is critically important. As detailed in Section 3, because academic qualifications are abundant in the applicant pool, it is the non-academic dimensions that often distinguish academically strong applicants from each other.[64] Exhibit 9 shows that, for a given level of academic achievement, White applicants are substantially more likely to have higher ratings across the three non-academic dimensions taken together.[65]

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accomplishments, such as significant family commitments or a physical disability. Applicants with profile ratings of 7, 8, or 9 are excluded from this analysis because those are not valid ratings according to the reading procedures (2018 Reading Procedures at HARV00015414 – 15). In my regression analysis, I treat such ratings as missing.

[63] See workpaper.

[64] Academic research has found that Asian-American high school students are more likely to apply to selective institutions than White high school students, even controlling for academic qualifications. In other words, even accounting for academic qualifications, a different sample of Asian-American and White high school students apply to institutions like Harvard. This differential behavior in the college application process is one possible reason why, on average, White and Asian-American applicants in the Harvard pool might exhibit different qualifications across the different dimensions Harvard evaluates. Sandra Black, Kalena Cortes, and Jane Lincove, "Apply Yourself: Racial and Ethnic Differences in College Application," NBER Working Paper #21368, 2015; Sandra Black, Kalena Cortes, and Jane Lincove, "Academic Undermatching of High-Achieving Minority Students: Evidence from Race-Neutral and Holistic Admissions Policies," *American Economic Review: Papers & Proceedings*, 105(5), 2015, pp. 604–610; Amanda Griffith and Donna Rothstein, "Can't Get There from Here: The Decision to Apply to a Selective College," *Economics of Education Review*, 28(5), 2009, pp. 620–628; David Card and Alan Krueger, "Would the Elimination of Affirmative Action Affect Highly Qualified Minority Applicants? Evidence from California and Texas," *Industrial and Labor Relations Review*, 58(3), 2005, pp. 416–434.

[65] In Appendix C of his report, Prof. Arcidiacono argues that "Harvard applies the label 'Standard Strong' disproportionately to Asian-American applicants" and that "Asian-American applicants who are labeled this way are substantially more qualified academically than 'Standard Strong' applicants from other racial groups." However, if one considers strength more broadly (as measured by the sum of all four profile ratings), Asian-American and White applicants who are labeled "Standard Strong" are equally strong. See workpaper.

Exhibit 9

For a given academic rating, White applicants tend to have better non-academic ratings than Asian-American applicants

		Share of Applicants with Non-Academic Ratings that Sum to 7 or Less		
	Academic Rating	**All**	**White**	**Asian-American**
1.	**1**	20%	25%	16%
2.	**2**	11%	14%	8%
3.	**3**	10%	12%	6%
4.	**4**	4%	6%	3%
5.	**5**	1%	2%	1%
	Total	9%	12%	7%

Source: Arcidiacono Data

Note: Data are from applicants to the classes of 2014 – 2019 in Professor Arcidiacono's expanded sample.

76. Exhibit 10 presents yet another way to measure the relative strength of White and Asian-American applicants on non-academic factors, using Prof. Arcidiacono's own model (specifically, his Model 6, with the overall rating excluded). In Table 7.3 of his report, Prof. Arcidiacono constructs an "admissions index," attempting to quantitatively summarize the overall qualifications of applicants based on *all* of the factors in his model.[66] In Exhibit 10, I have reproduced that same analysis but focusing only on the non-academic factors in his model. That is, I have removed from his admissions index the effect of the academic rating, grades, and all standardized test scores. The exhibit shows that, using Prof. Arcidiacono's own metric, Asian-American applicants are more likely than White applicants to have weaker non-academic qualifications (i.e. be in deciles 1 to 5), and that White applicants are more likely than Asian-American applicants to have strong non-academic qualifications (i.e. be in deciles 9 and 10). The same pattern is observed if I repeat this analysis but estimate the non-academic admissions index using Prof. Arcidiacono's Model 5, which excludes the personal rating.[67] In other words, Prof. Arcidiacono's own models show that White applicants are stronger than Asian-American applicants on non-academic dimensions, and this finding holds even if personal ratings (which Prof. Arcidiacono alleges are biased) are excluded from the non-academic qualifications.

[66] Arcidiacono Report, p. 68, Table 7.3.

[67] See workpaper.

Exhibit 10

White applicants rank higher than Asian-American applicants on non-academic admissions index

Non-Academic Admissions Index Decile	White	Asian-American	African-American	Hispanic
1. **5 or lower**	46.33%	51.12%	56.91%	54.60%
2. **6**	10.17%	10.45%	9.01%	9.33%
3. **7**	10.22%	10.46%	8.55%	9.27%
4. **8**	10.45%	10.42%	8.40%	8.82%
5. **9**	10.84%	9.65%	8.71%	9.03%
6. **10**	11.99%	7.89%	8.42%	8.95%

Source: Arcidiacono Data

Note: Data are from applicants to the classes of 2014 – 2019 in Professor Arcidiacono's expanded sample. The non-academic admissions index is constructed in the same fashion as Professor Arcidiacono's overall admissions index, using his model 6 without the overall rating to calculate applicants' probability of admission. Applicants with characteristics that guaranteed rejection or admission were assigned to the bottom or top decile, respectively. In addition to excluding the effect of race, as Professor Arcidiacono did, I exclude the effects of the academic rating and academic variables (such as Academic Index, SAT scores, and GPA).

77. As noted above, these facts are critical to the interpretation of Prof. Arcidiacono's model and SFFA's broader claim of bias. Throughout his report, Prof. Arcidiacono argues that, because Asian-American applicants have stronger academic credentials (on average) than White applicants, he can safely assume that they are also stronger than White applicants on dimensions of quality—mostly non-academic—that cannot be measured by his statistical model. If that were true, it would imply that adding more variables to Prof. Arcidiacono's model to further control for differences between White and Asian-American applicants would only *increase* the estimated negative effect of Asian-American ethnicity on applicants' probability of admission. But, as I have shown above, Prof. Arcidiacono's assumption is demonstrably incorrect.

78. In fact, although Asian-American applicants are stronger than White applicants (on average) on quantifiable measures of academic performance, they are (on average) less strong than White applicants on observable non-academic measures (Harvard's ratings and Prof. Arcidiacono's admissions index). Because non-academic factors are harder to quantify and include in the model than academic factors, any statistical model of the Harvard admissions process is therefore more likely to have more missing information about non-academic factors than about academic factors. And if the racial gap in the missing non-academic factors is similar to the racial gap in the measured non-academic factors (i.e., with Asian-American applicants having less strong qualifications than White applicants), then a statistical model of the admissions process will be predisposed to find a negative effect of Asian-American ethnicity on applicants' likelihood of admission, even though the

racial disparity in admission rates may actually be due to racial differences in the missing non-academic information.

4.3. Prof. Arcidiacono's model excludes available measures of life circumstance and context

79. In the remainder of this section, I highlight a set of important contextual factors—that is, factors that reflect the wide range of applicant characteristics that may inform admissions officers' evaluation of each application—that Prof. Arcidiacono excludes from his model and that differ, on average, between Asian-American applicants and White applicants. As I will show in Section 5, these contextual factors help explain the disparity in admission rates between Asian-American and White applicants, and when added to Prof. Arcidiacono's model lead to the conclusion that there is no statistically significant negative effect of Asian-American ethnicity on applicants' likelihood of admission.

80. As detailed above in Section 3, Harvard seeks to assess the quality of each applicant, in academic and non-academic respects, in light of the context provided by any available information about the challenges the applicant has faced, the resources at her disposal, and the opportunities she has (or has not) encountered. A major limitation of Prof. Arcidiacono's model is that it includes very few variables to account for these contextual factors. For example, Prof. Arcidiacono includes only a very limited set of socioeconomic variables, in addition to control variables that account for only broad differences across types of neighborhoods and high schools, as reflected in high school and neighborhood "cluster" numbers assigned by a proprietary algorithm of the College Board. Prof. Arcidiacono does not make use of the more detailed data about each individual high school and neighborhood that were produced along with the College Board's "cluster" identifiers and that inform the College Board cluster assignments.[68] For example, his model includes controls for 29 high school clusters, yet there are more than 14,000 high schools represented in the Harvard applicant pool.[69] Using the more detailed high school and neighborhood characteristics data can add meaningful information to the model.[70] As I show in this section, this modeling decision by Prof. Arcidiacono is problematic because Asian-American and White applicants (in aggregate) come from different sets of high schools and different regions of the country, have different career goals, and have different

[68] Prof. Arcidiacono's model includes the following socioeconomic controls: an indicator of whether the admission officer believed the applicant to be "disadvantaged," an indicator of whether the applicant applied for a waiver of the application fee, an indicator of whether the applicant applied for financial aid, an indicator of whether the applicant is in the first generation of his family to attend college, and indicators of the applicant's mother's and father's educational attainment.

[69] See workpaper.

[70] Additionally, Prof. Arcidiacono excludes a variable in the Harvard data indicating the type of high school an applicant attended (Archdiocese, Public, or Private). I include this variable in my models.

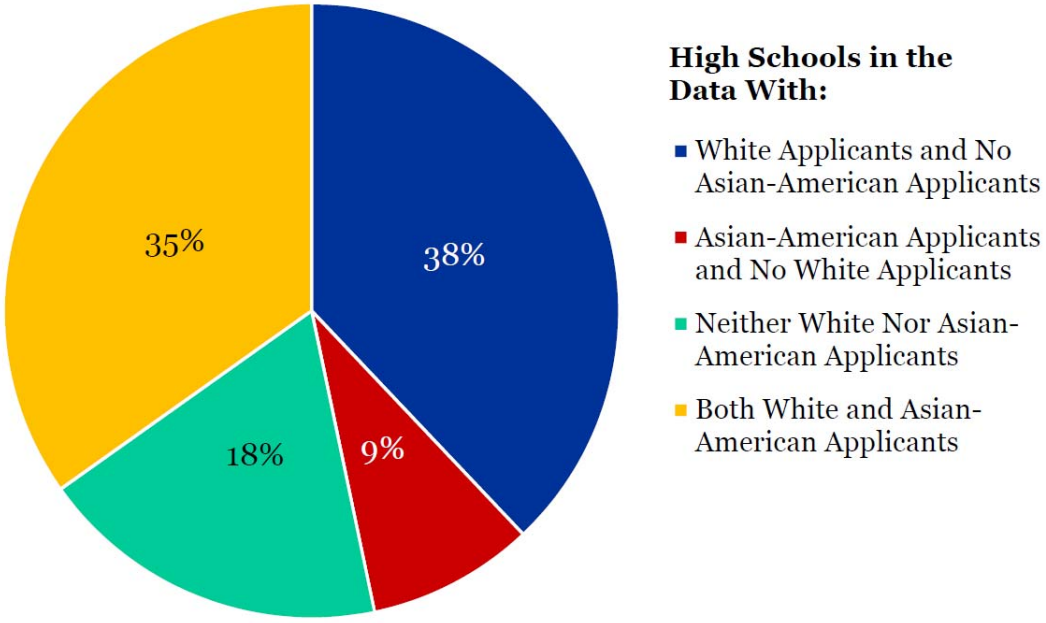
family backgrounds (such as parental occupations).

4.3.1. Detailed controls for differences across high schools and neighborhoods

81. As shown in Exhibit 11, Asian-American and White applicants come from very different sets of high schools. Nearly half of the high schools represented in the applicant pool have either White applicants but no Asian-American applicants or Asian-American applicants but no White applicants. This means that, without better controls in the model for high school characteristics, Prof. Arcidiacono is missing an important difference between the two groups.[71]

Exhibit 11

Asian-American and White applicants come from different high schools



Source: Arcidiacono Data

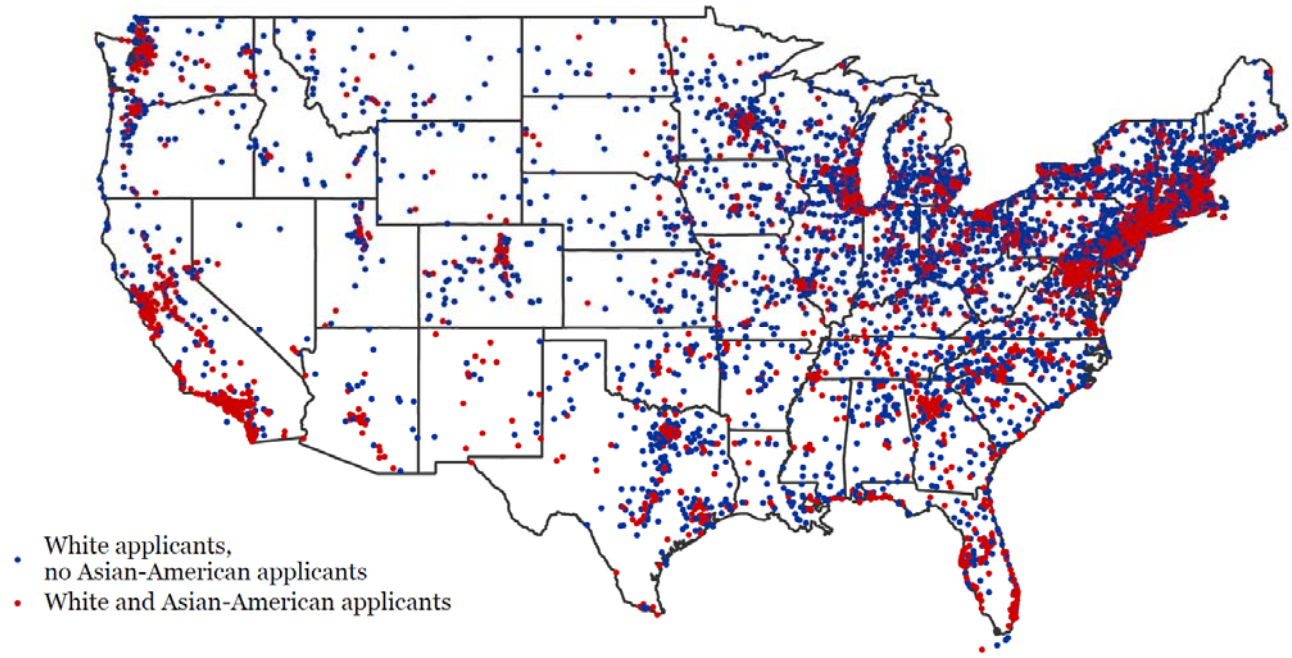
Note: Sample consists of Professor Arcidiacono's expanded sample.

[71] For example, high school characteristics include the high school's mean SAT score or the percentage of students in the high school who require financial aid for college. For a complete list of high school and neighborhood characteristics included in my model, see Appendix E. The College Board high school and neighborhood data report many high school and neighborhood characteristics based upon only the set of students from a given high school who take the SAT. Because the SAT is more common in some areas and the ACT in others, in my model I allow for these variables to have different effects in states where the SAT is more common than in states where the ACT is more common.

82. Asian-American and White applicants also come from different geographic regions. Asian-American applicants are more concentrated on the East and West coasts and in major cities. In fact, approximately 29% of all Asian-American applicants come from California dockets (dockets A, C, and Z), as compared to only 14% of White applicants.[72] Exhibit 12 highlights these differences by showing a map of all locations of Asian-American and White applicants' high schools. The blue dots indicate locations with White applicants but no Asian-American applicants (during the 2014 – 2019 admissions cycles). As is clear from Exhibit 12, there are a large number of blue dots in the central and rural areas of the U.S.

Exhibit 12

White applicants are more dispersed across the U.S. and rural areas



Source: Augmented Arcidiacono Data

Note: Sample consists of Prof. Arcidiacono's extended dataset for the classes of 2014 – 2019. Each blue dot represents the city of a high school from which at least one White applicant applied. Each red dot represents the city of a high school from which at least one Asian-American applicant and one White applicant applied.

83. Although Prof. Arcidiacono controls for an applicant's admissions docket (i.e., broad geographic region), he does not control for the much more detailed neighborhood attributes available in the College Board data, such as the median income of the neighborhood (defined as a census tract or collection of census tracts) or the proportion of students in a neighborhood who apply to an out-of-state college. Nor does he control for whether the applicant attends high school in a rural area or the

[72] See workpaper.

type of high school (public, private, or Archdiocese).

4.3.2. Other proxies for life experience, opportunities, and ambitions

84. In addition to ignoring the detailed available data on applicants' high schools and neighborhoods, Prof. Arcidiacono also fails to include in his model several available variables that reflect differences in applicants' family background and life goals.

85. For example, Prof. Arcidiacono ignores data on parental occupations, a critical measure of family background. As noted above, family background provides important context for each applicant's achievements. Exhibit 64 and Exhibit 65 (Appendix C) show that the parents of Asian-American and White applicants tend to have different types of occupations.[73] 33% of fathers and 16% of mothers of Asian-American applicants work in the fields of "Computer and Mathematical," "Life, Physical, Social Science," or "Architecture and Engineering," while only 16% and 5% (respectively) of fathers and mothers of White applicants work in those fields.

86. Such differences can reflect not just differences in a family's economic prosperity but also differences in applicants' life experiences. For example, if the son of a professional writer and the son of a police officer display talent in writing, Harvard might regard the latter's talent as more impressive than the former's. The same might be true of the daughter of professional scientists and the daughter of factory workers, both of whom exhibit talent in a scientific field. In fact, one of the examples from Harvard's casebook (discussed above in Section 3.2) specifically notes parental occupation as relevant context for evaluating her achievements: **Redacted**

87. Prof. Arcidiacono also excludes from his model other available data on applicants' family background, including whether an applicant's mother or father is deceased, whether one or both of the applicant's parents attended an Ivy League university, whether the applicant was born outside the United States, whether the applicant has lived outside the United States, whether the applicant is a permanent resident of the United States, and the hours an applicant spent working at a job.[74]

[73] In the Harvard database, applicants report parental occupations using either a Bureau of Labor Statistics (BLS) code or a Common Application code. Reported parental occupation codes are harmonized by mapping Common Application codes to major and minor groups in the BLS' Standard Occupational Classification System. Major and minor groups are then combined into broad occupational categories.

[74] Information on how much time an applicant spent working at a job and on whether an applicant was born outside the United States or lived outside the United States is available only for applicants to the classes of 2017 to 2019 and so can be included in my year-by-year model but not in Prof. Arcidiacono's pooled model.

88. Finally, Prof. Arcidiacono does not include a variable for intended career in his model. Exhibit 13 shows the differences in intended careers between Asian-American and White applicants. Asian-American applicants are much more likely to intend to pursue a career in medicine or health, while White applicants are much more likely to intend to pursue careers in the arts, communications, design, social service, government, or law. The difference in the intended career of medicine or health is particularly stark—White applicants are 37% less likely than Asian-American applicants to pursue this intended career, an intended career with the lowest admission rate (5%). As detailed above in Section 3.2, an applicant's future plans and fields of interest can be critical to the assessment of how the applicant will contribute to the Harvard community both inside and outside the classroom.[75] For example, the Casebook Discussion Guide notes the following about one candidate:
Redacted

[76]

Exhibit 13

White and Asian-American applicants have different intended careers

	Intended Career	Number of Applicants (All Races)	Share of White Applicants	Share of Asian-American Applicants	Percent Difference (White vs. Asian-American)	Overall Admission Rate (All Races)
1.	**Medicine or health**	35,915	19%	30%	-37%	5%
2.	**Science**	36,112	25%	26%	-5%	7%
3.	**Business**	14,503	10%	10%	-3%	6%
4.	**Other**	11,050	8%	6%	24%	8%
5.	**Teaching**	2,556	2%	2%	25%	10%
6.	**Undecided**	23,583	18%	14%	30%	10%
7.	**Government or law**	19,762	14%	9%	52%	8%
8.	**Arts, communications, design, or social service**	7,220	5%	3%	55%	8%

Source: Augmented Arcidiacono Data

Note: Data are from applicants to the classes of 2014 - 2019 in Professor Arcidiacono's expanded sample. The "Other" category includes applicants whose intended careers are academic, library, religion, trade, other, or unknown. Categories for intended careers can vary year to year.

[75] Another factor that reveals an applicant's interests is the type of extracurricular activities on which the applicant has focused in high school. Prof. Arcidiacono does not include any measure of the type of extracurricular activities in his model. As shown in Appendix D, there are significant differences across racial groups in applicants' primary activities (defined as those listed first or second on the application). Applicants are instructed to list the activities most important to them first on the Common Application. Information on activities is available in Harvard's data only for applicants to the classes of 2017 to 2019.

[76] Casebook Discussion Guide at HARV0018166.

89. Prof. Arcidiacono's decision to ignore available information related to non-academic considerations, including contextual factors, is particularly curious because his own regression models indicate that such variables can help explain differences in admission rates between Asian-American and White applicants. For example, as he adds measures of academic achievement to his model (moving from Model 1 to Model 2), the estimated negative association between Asian-American ethnicity and likelihood of admission increases. But as he adds more variables that capture the context of each candidate's application—such as broad high school and neighborhood demographics, and ratings that capture non-academic characteristics of the applicant—the estimated negative effect of Asian-American ethnicity shrinks substantially (Model 4 to Model 6).[77]

90. In the next section of this report, I show that the same general pattern holds in my model: As I add to the model the additional non-academic variables discussed in this section, the estimated negative effect of Asian-American ethnicity on applicants' likelihood of admission disappears. This finding is consistent with the hypothesis that what Prof. Arcidiacono labels a "bias" against Asian-American applicants in fact reflects not racial discrimination but differences in non-academic factors that Harvard considers in its whole-person evaluation.

[77] Arcidiacono Report, Appendix B, Table B.7.2.

5. A MORE COMPLETE STATISTICAL MODEL SHOWS NO EVIDENCE OF BIAS AGAINST ASIAN-AMERICAN APPLICANTS

91. As detailed in Sections 3 and 4 above, because Harvard's whole-person admissions process heavily considers non-academic and contextual factors that are often hard to measure, a statistical model that can reliably estimate the effect of race on Harvard's admissions decisions should seek to include as much reliable information about such factors as possible. In this section, I develop such a statistical model by starting with Prof. Arcidiacono's model and then expanding his set of control variables to include a richer set of characteristics that he did not include in his model, and that more fully capture the many factors that Harvard considers in its process. I further revise the model by allowing the coefficients it estimates for different control variables, which reflect the effects of different applicant attributes on the probability of admission, to vary from year to year. I then use this more complete model in the remainder of this report to address several questions at issue in this matter.

92. The first question I examine is whether the alleged negative association between Asian-American ethnicity and applicants' likelihood of admission persists when more information is included in the model. I find that it does not. When more variables are added to the model to capture differences in key contextual factors (high school, neighborhood, and family background), and when the model is estimated year-by-year to account for differences in the admissions process from year to year, the alleged negative effect of Asian-American ethnicity disappears and the predictive accuracy of my model increases.

93. I then turn to a second question in Section 6: to what extent does an applicant's race or ethnicity matter in the admissions process, relative to the many other factors Harvard considers in its whole-person analysis? While I find that race is significantly associated with the likelihood of admission for some applicants, the role it plays is less significant than that of other factors included in my model, as well as that of factors not observable in the model.

94. Before delving into the details of my analysis, I first discuss several important methodological issues that arise when building an admissions model, with a focus on differences between my approach and Prof. Arcidiacono's.

5.1. Important differences between Prof. Arcidiacono's methodology and mine

95. Prof. Arcidiacono uses a statistical model known as a multivariate logit regression to estimate the relationship between race and admissions outcomes, while controlling for a variety of

factors that Harvard considers in admission decisions.[78] The use of a multivariate logit model makes sense. Multivariate regression analysis is a widely accepted and common statistical technique in both academia and litigation.[79] Courts have relied on multivariate regression analysis in a variety of discrimination matters. In fact, the Reference Guide for Scientific Evidence dedicates an entire chapter to multivariate regression analysis, including applications to questions of discrimination.[80] A logit model is a type of multivariate regression model that is appropriate where, as here, the outcome of interest—in this case admission to Harvard—is binary, taking values of either zero (not admitted) or one (admitted).

96. Even though I agree with Prof. Arcidiacono's general approach, I disagree with several of the specific modeling decisions he makes when building his model. In the remainder of this section, I discuss these methodological decisions and explain why Prof. Arcidiacono and I reach different conclusions.

5.1.1. Inclusion of additional control variables

97. A basic tenet of econometric research is that the selection of control variables should be informed by the research question at hand and the specific outcome that is being modeled.[81] Thus, the first step in my analysis is to add to Prof. Arcidiacono's fullest models (Models 5 and 6) any variables missing from his models that Harvard considers in the admissions process.

98. As detailed in Sections 3 and 4 above, the most important feature of Harvard's decision

[78] William H. Greene, *Econometric Analysis* (Pearson, 2008), pp. 773–774 ("The probit and logit models are still the most common frameworks used in econometric applications."); Kenneth E. Train, *Discrete Choice Methods with Simulation* (The Cambridge University Press, 2009), p. 34 ("By far the easiest and most widely used discrete choice model is logit.").

[79] James H. Stock and Mark W. Watson, *Introduction to Econometrics* (Pearson, 2015), p. 189 ("The multiple regression model … permits estimating the effect … of changing one variable while holding the other regressors constant… provides a way to isolate the effect."); William H. Greene, *Econometric Analysis* (Pearson, 2008), pp. 8–10 ("The linear regression model is the single most useful tool in the econometrician's toolkit. The multiple linear regression model is used to study the relationship between a dependent variable and one or more independent variables. One of the most useful aspects of the multiple regression model is its ability to identify the independent effects of a set of variables on a dependent variable.").

[80] Daniel L. Rubinfeld, *Reference Manual on Scientific Evidence: Third Edition* (The National Academies Press, 2011), pp. 305–307 ("Regression analysis has been used most frequently in cases of sex and race discrimination, antitrust violations, and cases involving class certification.").

[81] James H. Stock and Mark W. Watson, *Introduction to Econometrics* (Pearson, 2015), pp. 232–234 ("The starting point for choosing a regression specification is thinking through the possible sources of omitted variable bias… A control variable is not the object of interest in the study; rather it is a regressor included to hold constant factors that, if neglected, could lead the estimated causal effect of interest to suffer from omitted variable bias.").

process that Prof. Arcidiacono's model does not account for is the substantial consideration Harvard gives to non-academic factors that help distinguish among the large number of academically strong applicants in its pool, including a wide variety of contextual factors that account for the life experience and background of each candidate (e.g., her high school, community, and family background).

99. The first panel in Exhibit 14 shows the variables that Prof. Arcidiacono includes in his fullest models (Models 5 and 6), while the second panel lists the additional variables I include in my model. Both sets of variables are organized into several broad groups: race, base controls (a category that includes personal and financial variables, such as an applicant's gender, docket, and parents' education), Harvard profile ratings (academic, extracurricular, personal, and athletic), other ratings (such as those assigned by admissions officers to recommendation letters from teachers or guidance counselors, or those assigned by alumni interviewers), measures of academic qualifications, high school and neighborhood characteristics, and interaction terms (such as interactions of race with gender that are included in Prof. Arcidiacono's models).[82] As shown, the additional variables that I add to my model include intended career; staff interview ratings; richer controls for high school and neighborhood characteristics;[83] parents' occupations; applicant's hours worked (at a job); controls for specific combinations of profile ratings, specific combinations of teacher ratings, and specific combinations of alumni interview ratings; indicators for participation in different types of primary extracurricular activities; and indicators for having parents who attended an Ivy League college, having parents who attended Harvard for graduate school, having a mother or father who is deceased, being a permanent resident of the United States, having been born in the United States, and having lived outside the United States.[84]

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[82] Appendix E provides a complete list of variables used in my model with detailed definitions.

[83] For the College Board high school and neighborhood variables most likely to be missing for applicants in the sample (neighborhood median income, proportion of neighborhood residents below poverty line, and neighborhood median housing value), I assign the mean value of the variable to those applicants who are missing data and include an indicator variable identifying those for whom the mean was assigned. This approach of imputing missing values is analogous to that used by Prof. Arcidiacono in his report.

[84] In my year-by-year models, there is not enough data to estimate separately the effect of some of the specific ratings that are very rare in the data due to limited sample size. To resolve this problem, rather than include a separate dummy variable for each individual rating category, I include a dummy variable for each unique *combination* of the four profile ratings, each unique combination of the two teacher ratings, and each unique combination of the alumni interviewer ratings. Unique ratings combinations with fewer than 100 observations are grouped with other ratings combinations such that the combination is in a group that has an admission rate most similar to that of the combination. I have confirmed that this approach has no substantive effect on the estimated size of the Asian-American coefficient and yields nearly the same predictive accuracy as Prof. Arcidiacono's approach in the pooled model. (See workpaper.) Additionally, as I explain below, my year-by-year models using this approach more accurately predict Harvard's admissions decisions than Prof.

100. I also make a series of more technical corrections to Prof. Arcidiacono's variables and sample. First, Prof. Arcidiacono includes a number of variables that he interacts with race and gender in his model.[85] An "interaction" variable simply multiplies one variable by another variable, to show how the presence or absence of the second variable modifies the effect of the first. For example, one could model the effect of male gender on the likelihood of admission, the effect of Asian-American ethnicity, and the effect of male gender *and* Asian-American ethnicity—that is, the extent to which being male decreases or increases the effect of being Asian American, and vice versa. Since there are hundreds of potential interactions one could add to the admissions model, and it is not computationally feasible to include all of them, it is unclear why Prof. Arcidiacono chose to include specific interactions—for example, allowing the effect of gender and "disadvantaged" status to vary by race—and not others. Decisions to add interactions to a model like Prof. Arcidiacono's are typically guided by a clear economic theory or methodological goal. The typical approach in a model trying to isolate the effect of Asian-American ethnicity on admissions outcomes would be to include an interaction between race and disadvantaged status only if the effect of being disadvantaged is different for Asian-American and White applicants (or, equivalently, if the effect of race is different for disadvantaged and non-disadvantaged applicants). Prof. Arcidiacono's results, however, show that is not the case. In my model, I remove the interactions with race and gender. This is a more transparent approach that requires fewer subjective judgments about which of the hundreds of interactions that can be included in such a model should be included.

Arcidiacono's pooled model. This approach has the additional benefit that it can account for any potential "interaction" effects associated with specific combinations of the four ratings profiles.

[85] Arcidiacono Report, p. 62.

Exhibit 14

Control variables used in logit models of admission

Professor Arcidiacono's Models 5 and 6	Additional Variables in Card Models
Race Variables	
Race *(White, African-American, Hispanic, Native American, Hawaiian/Pacific Islander, Asian-American, and Missing)*	
Base Control Variables	
Year, gender, docket	Mother and father occupation
First generation college	Mother or father deceased
Disadvantaged, fee waiver, and financial aid	Parent attended Ivy League college
Dean or Director's interest list†	Rural applicant
Mother and father education level	Intended career
Early Action†	School type *(public, private, Archdiocese)*
Athlete†, legacy†, double legacy†	Parent attended Harvard Graduate School
Child of Harvard faculty or staff†	Born in United States, lived outside of United States
	Permanent resident of United States
	Primary extracurricular activity indicators
	Total hours of work
Interactions	
Race and intended concentration interacted with gender*	
Disadvantaged, early decision†, and legacy† interacted with race*	
Missing data indicators interacted with race*	
Profile Ratings	
Academic, extracurricular, and athletic ratings	Profile rating combinations
Personal rating (Model 6 Only)	
Other Ratings	
Alumni interview ratings	Alumni interview ratings combinations
Teacher ratings	Teacher ratings combinations
Guidance counselor rating	Staff interview ratings
Overall rating (Model 6 Only)*	
Academic Variables	
ACT/SAT Math and Verbal, Average SAT Subject Test Score	
Converted GPA and indicator for value of 35	
Academic Index Quadratic	
High School and Neighborhood Characteristics	
High school cluster ID*	High school characteristics *(such as average SAT math)*
Neighborhood cluster ID*	Neighborhood characteristics *(such as median income)*
	SAT state indicator
Missing Data Indicators	
Alumni interviewer rating*, cluster IDs*, and Average SAT Subject Test Score	

Legend:
* Removed from Card Models.
† Included in expanded sample model only.

Source: Augmented Arcidiacono Data

101. I also correct a variety of technical errors in Prof. Arcidiacono's sample and control variables:

- Prof. Arcidiacono treats profile ratings of 7, 8, and 9 as low ratings, but 7, 8, and 9 ratings do not appear in the reader guidelines and thus are more likely erroneous data entries.[86] I treat such entries as missing ratings.
- Prof. Arcidiacono drops applicants with blank teacher ratings from his regressions, rather than including them in the "missing" category of his teacher ratings variables. I include such entries in the "missing" category.
- Prof. Arcidiacono makes an error when importing the ACT science scores. I correct this error so that they are imported correctly.
- I remove sample conditions related to the overall rating since the overall rating is excluded from all of my models and thus there is no need to exclude applicants with low or missing overall ratings.[87]

5.1.2. A year-by-year model is more appropriate than a pooled model

102. Another important methodological flaw in Prof. Arcidiacono's approach is his decision to pool admissions data across years. This decision is flawed for several reasons.

103. First, the admissions process at Harvard is, by its nature, an annual process. Each applicant is compared to other applicants who applied in that year. A pooled analysis does not reflect how the process actually works, because it effectively compares applicants from different years to each other.

104. Second, a closely related problem with a pooled model is that it imposes the assumption that every factor in the admissions process has the same effect from year to year. Given that the applicant pool changes from year to year, it is quite possible that the relative abundance and scarcity

[86] 2018 Reading Procedures at HARV00015414 – 15.

[87] As noted above, I also exclude the overall rating from all of my models. As discussed above, according to deposition testimony in this case, race can influence the overall rating. Since my analysis seeks to isolate the incremental effect of race on admissions decisions, it is inappropriate to include any variables that can themselves be affected by race. Removing the overall rating from my model is a conservative approach because White applicants have slightly higher overall ratings, on average, than Asian-American applicants. My analyses show that, even without the inclusion of overall rating in the models, there is no evidence of bias in admissions decisions.

of relevant factors can also change, which can cause the value Harvard places on any given factor to also change from year to year. Below I provide several examples of how this dynamic might play out.

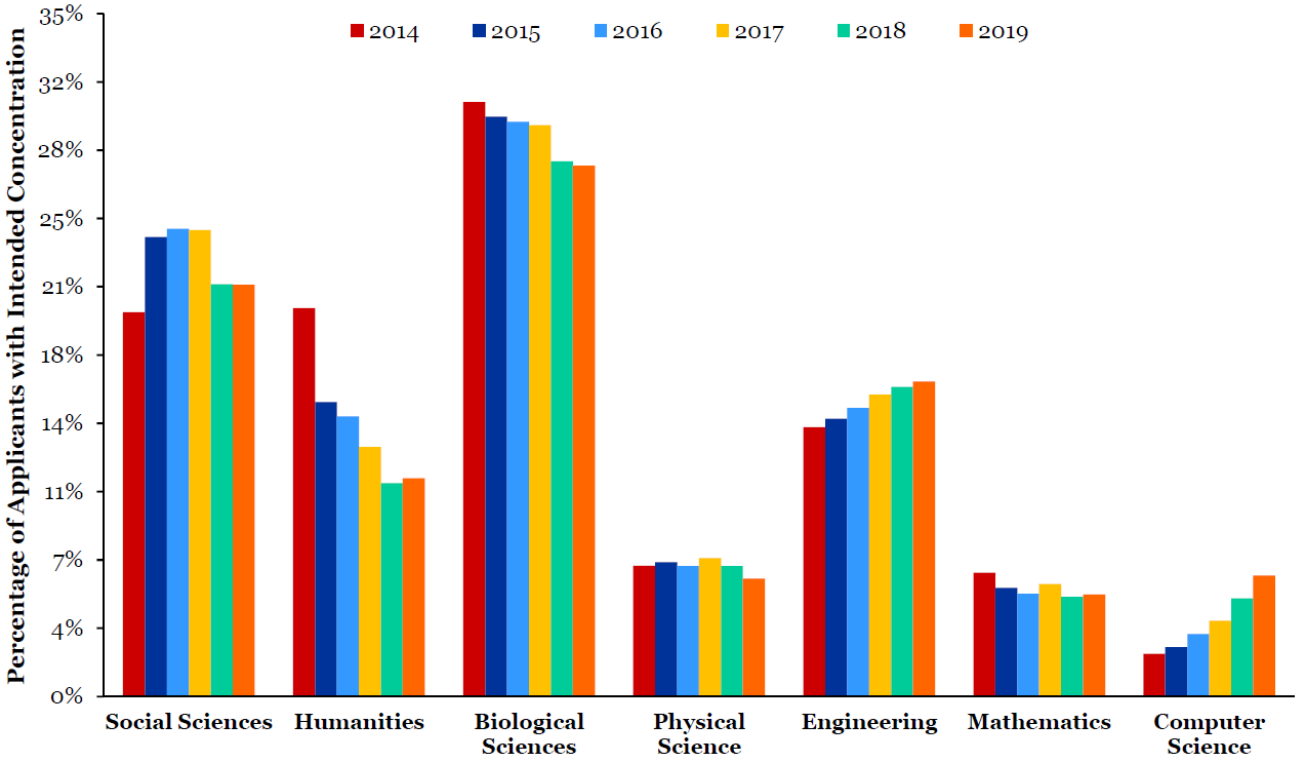
105. One example is that, during the period for which I have data, Harvard saw a shift in applicants' intended concentrations. (See Exhibit 15.) **Redacted**

[88] Because Harvard seeks to admit a class that is diverse with respect to intended concentrations, the effect of an applicant's intent to concentrate in a given field might well change when the aggregate interests of the applicant pool as a whole vary over time. Thus, for example, an applicant's intention to concentrate in the humanities might distinguish an applicant more or less depending on the overall mix of intended concentrations in the applicant pool in that year.

[88] One potential factor contributing to this shift in intended concentrations is that in 2007, Harvard elevated the Division of Engineering and Applied Sciences to the School of Engineering and Applied Sciences. John A. Paulson School of Engineering and Applied Sciences, "Timeline," available at https://www.seas.harvard.edu/about-seas/history-seas/timeline, accessed November 20, 2017.

Exhibit 15

The mix of intended concentrations for Harvard applicants has changed over time



Source: Augmented Arcidiacono Data

Note: Sample consists of applicants to the classes of 2014 – 2019 in Prof. Arcidiacono's corrected expanded sample. Applicants with missing and "Unspecified" intended concentrations are excluded from this chart.

106. Another example is that the definition of the dockets (the geographical divisions Harvard uses in its admissions process) changed during the time period for which I have data. Starting with the class of 2015, Harvard introduced the J docket. For the classes of 2015 – 2019, the J docket included applicants from Arkansas, Kansas, Kentucky, Mississippi, Missouri, Western New York, Oklahoma, Tennessee, and West Virginia, but for the class of 2014 those applicants were distributed across other dockets.[89] Prof. Arcidiacono's model cannot account for this change because it estimates the effect of an applicant's docket placement on admission only after pooling years together. Thus, his model estimates docket effects incorrectly because it conflates the two different definitions of

[89] See workpaper.

dockets across years.

107. Additionally, as I discuss in greater detail in Section 7 below, Harvard did not employ an Early Action admissions process for the classes of 2014 and 2015. Starting with the class of 2016, it reinstated Early Action.[90] Prof. Arcidiacono's model cannot account for these changes because he pools all the data together into a single model. As a result, the estimated effect of each variable in his model is calculated using two different admissions regimes—one in which Early Action admissions existed and one in which it did not. That is problematic for both his expanded and baseline samples. Excluding Early Action applicants, as he does in his baseline sample, is not sufficient to correct for the problem, because there is no way to identify which applicants would have applied Early Action had Early Action existed.

108. Variation in the admission rate across the six admission cycles for applicants with the same profile ratings combinations provides further justification for estimating the model year-by-year. For example, consider applicants with ratings of 2 on all four dimensions (academic, extracurricular, personal, and athletic). Applicants with this ratings combination have an admission rate that varies between 61% and 77% depending on the admissions cycle.[91] By pooling data across year, Prof. Arcidiacono's model assumes these ratings have the same effect in each year.

109. To formally test whether the effect of various applicant characteristics on applicants' likelihood of admission is sufficiently similar across years to justify using a "pooled" model as Prof. Arcidiacono does, I have employed a standard statistical test known as a Wald test (or a chi-squared test). That test is designed to evaluate the null hypothesis that applicant characteristics have identical effects on likelihood of admission from year to year. I find that the Wald test rejects that null hypothesis here, indicating that a pooled model is inappropriate.[92] Additionally, as I will discuss in more detail below, I find that my year-by-year models are better able to predict admission, a further justification of using year-by-year models rather than a pooled model. Given these results, and the fundamental fact that Harvard's admissions decisions are made separately for each year, the

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[90] Harvard Office of Institutional Research presentation, "Admissions and Financial Aid at Harvard College," February 2013, HARV00031687 – 1772 ("OIR Presentation") at HARV00031695.

[91] See workpaper.

[92] To implement this test, I start with Prof. Arcidiacono's Model 6 for the expanded, pooled sample, and exclude the overall rating and interactions with race and gender. I then interact all other control variables with each of his dummy variables for each year to directly test whether the effects of the control variables change from year to year. In implementing the test, I combine Native American and Hawaiian/Pacific Islander applicants with Hispanic applicants and combine personal ratings of 1 and 2 into one dummy variable because there are too few applicants in those categories to allow me to interact each variable with each separate year dummy. See workpaper.

methodologically sound approach is to estimate a separate model for each year.[93]

5.1.3. Definition of race

110. In my analysis, I generally use the same method for classifying applicants by race as Prof. Arcidiacono uses, to ensure comparability of results. However, when estimating a separate model for each year, I have to combine one race group with another due to the fact that there are very few applicants of a particular race (e.g., Native American or Hawaiian/Pacific Islander) in any one year.[94] In Prof. Arcidiacono's model, applicants are classified into mutually exclusive categories of White, African-American, Hispanic, Native American, Hawaiian/Pacific Islander, Asian-American, and Missing.[95] In my year-by-year models, I use the following mutually exclusive race categories: (1) White, (2) African-American, (3) Hispanic, Native American, or Hawaiian/Pacific Islander, (4) Asian-American, and (5) Missing.[96] I combine Native American and Hawaiian/Pacific Islander applicants with Hispanic applicants because the increased probability of admission associated with Native American and Hawaiian/Pacific Islander ethnicity is most similar to the increased probability of admission associated with Hispanic ethnicity.[97] To ensure that my estimate of the alleged bias against Asian-American applicants is robust to this change, I have tested whether using this adjusted definition of race has any substantive effect on the Asian-American coefficient within Prof. Arcidiacono's pooled sample. It does not.[98]

111. I have also considered the possibility (raised by Prof. Arcidiacono) that the fact that some applicants to Harvard are not classified as belonging to any racial group (i.e. are "Missing" race) might lead to an underestimate of the alleged bias against Asian-American applicants. For the purpose of this analysis, I use other variables in the Harvard data with information about an applicant's race that Prof. Arcidiacono did not use in creating his definition of race. For example, if

[93] Prof. Arcidiacono himself finds evidence that it is better to estimate the model separately for each year. For example, he presents a model in his report using the expanded sample in which he interacts year and race (thus allowing each race to have a separate effect in each year). That model finds that the effect of race differs in a statistically significant fashion across years (Arcidiacono Report, Appendix B, Table B.8.1).

[94] Prof. Arcidiacono also combines smaller race groups when he estimates a model that interacts his race categories with year (Arcidiacono Report, p. 69, footnote 69).

[95] This race definition is a variable available in the Harvard database. In 2010, Harvard began using an additional methodology that allows applicants who self-identified with more than one race to be counted in more than one category (Deposition of Elizabeth Yong, March 24, 2017 ("Yong Deposition"), pp. 134–137).

[96] I also combine Hawaiian/Pacific Islander applicants with Asian-American applicants, rather than grouping them with Hispanic applicants, in a sensitivity of my preferred model (discussed in more detail below).

[97] See workpaper.

[98] See workpaper.

an applicant reports her race to the College Board when taking the SAT, it is provided to Harvard along with the test score. Using these variables, it is possible to identify the race of many applicants that are classified as missing race in Prof. Arcidiacono's analysis. In fact, I am able to classify nearly 70% of the 10,000 applicants classified as having a "missing" race.[99] When I re-estimate Prof. Arcidiacono's model with these additional applicants' race information filled in, I find that in fact his estimates of the effect of Asian-American ethnicity become slightly less negative, not more.[100] That directly contradicts Prof. Arcidiacono's claim that the exclusion of these applicants' races likely causes his model to underestimate the bias against Asian-American applicants.

5.1.4. Prof. Arcidiacono's Models 1-4 are not reliable

112. Prof. Arcidiacono offers six different models to estimate the effect of Asian-American ethnicity on the probability of admission. My analysis builds exclusively on Prof. Arcidiacono's Models 5 and 6, for two reasons.

113. First, Prof. Arcidiacono states that "Model 5 is the most useful of [his] models for determining the effect/impact of race in admissions decisions,"[101] and Mr. Kahlenberg uses Model 6 as his preferred model for simulating race-neutral admissions practices. SFFA's own experts thus agree that Models 5 and 6 are the most reliable.

114. Second, as explained above, Models 1, 2, 3, and 4 are unreliable because they do not account for any of Harvard's ratings on non-academic dimensions. As detailed in Section 3 above, Harvard's admissions process considers a wide variety of non-academic factors, and non-academic excellence is rarer in the Harvard applicant pool than academic excellence. Harvard's profile and school-support ratings play an essential role in capturing non-academic information, much of which is not otherwise quantified. Because Prof. Arcidiacono's Models 1–4 ignore that critical information, they cannot reliably estimate the effect of race.

115. Exhibit 16 helps illustrate this point. It reports the Pseudo R-Squared value for each of Prof. Arcidiacono's Models 1–6. The Pseudo R-Squared statistic provides a useful summary measure of the extent to which the variables included in a model explain the outcome being modeled (in this case, admission to Harvard). It can take on values ranging from zero to one; the closer it is to one, the more the model explains about Harvard's admission decisions. Models 1–4 have Pseudo R-Squared

[99] See workpaper. Although I understand that admissions officers rely on applicants' self-identification of their race on the application (see Deposition of Grace Cheng, April 7, 2017, pp. 114–115; Banks Deposition, p. 190; Fitzsimmons Deposition, pp. 239–240), I use race information reported by the applicant on the SAT, SAT II, and ACT tests for the limited purpose of this sensitivity analysis. I do not include this additional race information in the rest of my models.

[100] See workpaper.

[101] Arcidiacono Report, p. 62.

values of 0.34 or lower—very low, and much lower than the Pseudo R-Squared values of Models 5 and 6, which jump to 0.57 and 0.65, respectively (for the expanded sample). That is because Models 1–4 ignore critical information on which Harvard relies when making admission decisions.

Exhibit 16

Explanatory power of Professor Arcidiacono's logit models of admission

	McFadden Pseudo R-Squared	
Model	**Baseline Model**	**Expanded Model**
1. **1**	0.04	0.19
2. **2**	0.23	0.33
3. **3**	0.24	0.34
4. **4**	0.25	0.34
5. **5**	0.53	0.57
6. **6**	0.62	0.65

Source: Arcidiacono Report, Appendix B, Tables B.7.1 and B.7.2.

5.1.5. The expanded sample is more appropriate than the baseline sample

116. Prof. Arcidiacono presents his models using two different samples—one that he refers to as the "baseline sample" and one that he refers to as the "expanded sample." The baseline sample removes lineage applicants, recruited athletes, children of Harvard faculty and staff, candidates who appear on the Dean's or Director's interest lists, and Early Action applicants. My analyses rely on the expanded sample, for several reasons.

117. First, as a general matter, Harvard compares all of its applicants in each year to all other applicants in the pool for that year; it does not conduct separate admissions processes for discrete subsets of the pool. Harvard seeks a diverse class in each year on any number of dimensions—academic, extracurricular, geographic, racial and ethnic, and so on. Thus, the fact that some candidates with particular attributes (such as lineage applicants or recruited athletes) have a higher likelihood of admission does not mean that they should be completely excluded from the analysis. Such candidates are still compared to other candidates on all dimensions, and their candidacy can affect how other decisions are made. By throwing such information out of the analysis, the model cannot use that information to explain why other applicants were or were not admitted.

118. This methodological flaw is particularly a concern for Prof. Arcidiacono's decision to remove from his baseline sample applicants for Early Action admission. This decision is inconsistent with how Harvard's admissions process works. It is my understanding that Harvard does not have a

different standard for admission in the Early Action process, and most applicants who apply early and are not admitted have their applications "deferred" to the Regular Decision phase,[102] where they compete with applicants who did not apply early.[103] Removing early applicants from the sample thus has the effect of modeling only part of the regular admissions cycle, excluding many applicants with whom the included applicants are competing for spots.

119. Second, as noted above, the Early Action process did not exist in two of the years of data used in Prof. Arcidiacono's model. Thus, for years in which there was no Early Action process (the class of 2014 and 2015 admissions cycles), Prof Arcidiacono's "baseline sample" includes a different set of applicants than in years for which Early Action was available. Further, because Prof. Arcidiacono pools data across all years and then *excludes* Early Action applicants for years in which Early Action existed, his baseline sample combines multiple years of data that have different definitions of a "baseline" sample, creating a pooled sample that is inconsistent. That is a major problem with his "baseline" sample and pooled model.

120. Finally, because it is important to estimate the models separately by year, limiting the sample to Prof. Arcidiacono's "baseline" sample unnecessarily reduces the sample size of the year-by-year models, which reduces the power and precision of the models.

5.1.6. The importance of factors that Harvard values but that are not measured in the data

121. As detailed throughout this report, Harvard's admissions process considers non-academic factors that are relatively scarce in the applicant pool and difficult to quantify in a regression model. Even after enriching my admissions model to capture a variety of such factors that are missing from Prof. Arcidiacono's model (and to improve its predictive power relative to Prof. Arcidiacono's model), my model still does not perfectly explain all of Harvard's admissions decisions. This implies that there are additional factors not measured by my model that are important

[102] See workpaper.

[103] McGrath Deposition 2015, p. 210 ("Q. And then everything we just said about the information that gets presented to the subcommittee is the same for regular action as it is for early action? A. Yes."); Weaver Deposition, Volume II, pp. 172–173 ("Q. Besides the timing, what other variations are there between …early action and regular action? … A. There are differences between the two in the sense of timeline and the quantity of applications; however, the process and the way in which a folder moves through the process is similar."); Ray Deposition, p. 55 ("Q. When you go to subcommittee in the regular action review process, …do you follow the same format that you did in early action review? … A. Yes. … Q. And do you typically give the same designations for students—namely, admitted, wait list, rejected, FAO hold—during the subcommittee process and regular action review? ... A. Yes. The only different action is that there is no defer action in regular action.").

to Harvard's admissions decisions. The omission of such factors from the model presents a classic example of a problem known as "omitted variable bias," or what I have referred to above as the "missing data" problem.[104]

122. Omitted variable bias occurs whenever a regression model omits variables that (1) are correlated with the variable of interest and (2) affect the outcome variable. In that circumstance, the effect of the omitted variable on the outcome may incorrectly be attributed to the variable of interest. Here, the variable of interest is race, so the omission of variables that are correlated with race and affect admissions outcomes—such as the non-academic factors discussed throughout this report—can lead the model to misattribute to race differences in admissions outcomes that are in fact attributable to the omitted variables.

123. Statistical methods can help quantify the importance of unmeasured, individualized factors in the decision process relative to factors that are more easily measured. These methods can help us understand the degree to which factors outside of the model might bias the results, and/or explain the reasons a specific applicant was ultimately admitted or denied admission. Below are four widely accepted methods that I will use in the remainder of this section, and that will be important in showing that Prof. Arcidiacono's model is missing critical information.

- Measures of overall fit and predictive accuracy: These statistics measure how well the model explains, or predicts, the outcome of interest (in this case, admission to Harvard). I will rely primarily on two such metrics. The first is Pseudo R-Squared, a measure of how well the variables included in the model explain the outcome. The second is the fraction of admitted applicants for whom the model correctly predicts the actual admission outcome.[105]

- Predicted probability of admission for each *individual* applicant: Whereas the metrics discussed above reflect how well the model

[104] James H. Stock and Mark W. Watson, *Introduction to Econometrics* (Pearson, 2015), pp. 183–184 ("If the regressor is correlated with a variable that has been omitted from the analysis and that determines, in part, the dependent variable, then the OLS estimator will have omitted variable bias."); Sharmila Choudhury, "Reassessing the Male-Female Wage Differential: A Fixed Effects Approach," *Southern Economic Journal* 60(2), 1993, pp. 327–340 at p. 327 ("The conventional approach of economists has been to estimate earnings as a function of various socio-economic characteristics. The observed wage gap is decomposed into a part explained by productivity related factors and an unexplained residual, traditionally labelled as discrimination. While it is possible that the unexplained variation earnings is the result of discrimination, it is also possibly the result of model misspecification ... we address the misspecification that could possibility arise from omitted variables…").

[105] Because the logit model estimates a probability of admission for each applicant, I compute this statistic by ranking applicants from highest to lowest predicted probability of admission and considering the top-ranked applicants to be admitted, such that the number of predicted admitted students matches the number of actual admitted students.

explains admissions outcomes in *aggregate*, the importance of unmeasured factors in any *individual* admissions decision can be quantified using the estimated probability of admission for each individual applicant. For example, if the model generates an estimated probability of admission close to zero for an applicant who is actually admitted, or vice versa, it suggests that there are unobserved factors that substantially affected the admission outcome. A particularly useful exercise is to compare the predicted probability of admission for any given applicant to the final admission decision. The difference between the predicted probability of admission and the actual admission decision is a measure of the importance of unobserved factors that are valued by admissions officers but not included in the model. The larger the difference, the more important unobserved factors were in the final decision.

- Sensitivity of coefficients to inclusion/exclusion of additional control variables: Another way to assess the influence of unmeasured factors on a given outcome variable is to estimate "sensitivity" analyses that include different sets of control variables, testing how the effect of a particular variable of interest changes when different sets of controls are included. Prof. Arcidiacono employs this analysis himself when using his Models 1–6, as will I in order to better understand the effect of factors that cannot be included in my estimation.

- Subgroup analysis: A closely related method for assessing the importance of unmeasured factors is subgroup analysis. If racial bias is the cause of a disparity between racial groups in an outcome like admission to Harvard, then one would expect to see the disparity persist across *all* relevant subgroups, time periods, and outcomes in the data. For example, a bias against applicants of a particular race should affect men and women of that race alike, and should affect members of that race across all years, since race is consistent across gender and time. On the other hand, if the racial disparity is caused by unobserved factors rather than by bias, it is much more likely that the disparity will vary across subgroups because, simply by chance, the relative strength and weakness of each racial group on unmeasured factors will differ by subgroup. Similar logic applies if the disparity at issue is not consistent across different outcome measures—if the admissions process is in fact

biased, there should be consistent evidence of bias not just in ultimate admissions decisions but in other types of outcomes that reflect the judgment of admissions officers, such as profile ratings. I employ these types of analyses in Section 5.3 below.

5.1.7. The importance of average marginal effects

124. One final technical note warrants discussion. In the appendix tables of his report, Prof. Arcidiacono reports only the logit coefficients of the race variables from his regression models. Those coefficients show the marginal effect of a given variable (e.g., an indicator for Asian-American ethnicity) on the logarithm of the odds (the so-called log-odds) of admission, rather than the marginal effect of a given variable on the *probability of admission* for a given candidate. Importantly, in a logit model, the marginal effect of any given variable on an applicant's probability of admission varies depending on that applicant's other characteristics, and there is no single parameter that measures the gap in admission probabilities between different subgroups. As a result, simply reporting the logit coefficient for a given variable does not convey the effect of that variable across all applicants in the relevant population (here, Asian-American applicants).

125. For example, consider an applicant to Harvard who has an academic rating of 4 or worse. She will have very little chance of admission given Harvard's high academic standards. Thus, even if she was very active in her high school, served as president of the student government, and volunteered at numerous community organizations (all characteristics Harvard values), she would still have very little chance of admission. Those factors will have essentially zero marginal effect on her probability of admission. On the other hand, if the same candidate had an academic rating of 1 or 2, then the marginal effect of her strong extracurricular and community service record on her probability of admission would be much larger. This is what is referred to as a "non-linear" effect—the effect of the student's non-academic achievements depends on whether her academic qualifications are strong enough for her to be in the running.

126. Because of these non-linear effects, the typical way to summarize the marginal effect of a variable in a logit regression is to report its *average* marginal effect across all individuals who possess the trait in question—rather than simply reporting its logit coefficient, as Prof. Arcidiacono does.[106] For example, in the hypothetical above, one would report the average marginal effect of a

[106] A. Colin Cameron and Pravin K. Trivedi, *Microeconometrics: Methods and Applications* (Cambridge University Press, 2009), pp. 467, 501 ("[T]here are several ways to compute an average marginal effect. It is best to use …the sample average of the marginal effects…Typically these [marginal effects] are then averaged over individuals to give an average marginal effect[.]"); William H. Greene, *Econometric Analysis* (Pearson, 2008), p. 775 ("For computing marginal effects, one can evaluate the expressions at the sample means of the data or evaluate the marginal effects at every observation and use the sample average of the individual marginal effects…Current practice favors averaging the individual marginal effects when it is possible to do so.").

candidate's extracurricular achievements across all candidates. If the average marginal effect of a given variable is not statistically different from zero, one can conclude that on average the variable does not have a significant effect on the outcome of interest. For this reason, I report all effects of race in my report as average marginal effects.

127. Another shortcoming of Prof. Arcidiacono's approach to reporting the logit coefficients is that, because he estimates the effect of Asian-American ethnicity separately for men and women and for those who are and are not identified by Harvard's admissions officers as disadvantaged, most of his analysis does not quantify the overall effect of ethnicity for the full set of Asian-American applicants.[107] The Asian-American logit coefficient (-0.367) that he reports in his appendix table B.7.1 and discusses in Section 3.7 of his report actually refers to the effect of Asian-American ethnicity *only for male applicants who are not disadvantaged*, not the effect for the general population of Asian-American applicants, including those who are disadvantaged and those who are female.[108] To calculate the effect on the log-odds of admission of Asian-American ethnicity for non-disadvantaged female applicants, for example, one must add together the Asian-American coefficient and the Asian-American*female coefficient, yielding an effect on the log-odds of only -0.089—less than one-quarter the size of the effect that Arcidiacono misleadingly reports.[109] Calculating an average marginal effect, as I do throughout this report, corrects this problem by reporting a single, average estimated effect of Asian-American ethnicity on likelihood of admission across all Asian-American applicants.

5.2. My enriched model finds no statistically significant evidence of bias

128. I now turn to the results of my statistical model. As detailed above, I start with Prof. Arcidiacono's model and then include a richer set of control variables that he does not include in his model and that more fully account for the substantial consideration Harvard gives to non-academic factors, including contextual factors like high school, neighborhood, and family background. I then use the model to test whether the disparity between Asian-American and White admission rates can be explained by factors in the model other than race. As I show below, once additional relevant factors are included in the model, Asian-American ethnicity has no consistent statistically significant

[107] Prof. Arcidiacono's Table 7.2 is an exception.

[108] This also applies to Prof. Arcidiacono's Table B.7.2 and various other tables reporting logit coefficients in his report, such as those for his ratings regressions. Additionally, he includes interactions between race and missing variable indicators for variables such as SAT II average, alumni interview rating and College Board cluster identifiers, so the coefficients he reports are actually for Asian-American non-disadvantaged male applicants who are not missing these covariates.

[109] -.089 = -.367+.278 summing logit coefficients on Asian-American and female*Asian-American from Prof. Arcidiacono's Table B.7.1.

negative effect on applicants' likelihood of admission.

5.2.1. With better and more complete control variables included in Prof. Arcidiacono's regression model, there is no statistically significant gap in admission rates between Asian-American and White applicants

129. Exhibit 17 presents one of the key findings of my analysis: The alleged effect of Asian-American ethnicity on applicants' likelihood of admission is statistically insignificant even in a model that pools all applicants across years as Prof. Arcidiacono does.

130. Each row in Exhibit 17 reports the average marginal effect of Asian-American (relative to White) ethnicity for a particular specification of Prof. Arcidiacono's Model 6, including the additional changes I make to Model 6 described above. The average marginal effect is the average change in the estimated probability of admission associated with being Asian-American as opposed to White, calculated across all Asian-American applicants in the sample.

Exhibit 17
Pooled logit models of admission do not show evidence of bias against Asian-American applicants

Model	Average Marginal Effect of Asian-American Ethnicity
1. **Professor Arcidiacono's model 6**	-0.46 *
2. **Remove overall rating only**	-0.58 *
3. **Remove all interactions and overall rating**	-0.53 *
4. **Card pooled model**	-0.14

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Table shows the average marginal effect of race on admission for Asian-American applicants. The Card pooled model uses Professor Arcidiacono's corrected expanded sample; all other models use Professor Acidiacono's expanded sample. Marginal efects are calculated relative to White applicants (using the same definition of race as Professor Arcidiacono). * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

131. The first row is calculated directly from Model 6 in Prof. Arcidiacono's report. It shows that the average marginal effect of Asian-American ethnicity in Model 6 is -0.46. This means that, relative to the average White applicant, the average Asian-American applicant has a lower probability of admission to Harvard—by 0.46 percentage points—controlling for all of the variables in Prof. Arcidiacono's model. This effect is statistically significant.

132. The second row also relies on Prof. Arcidiacono's Model 6, but removes the overall rating, which should not be included in any model that is attempting to estimate the effect of race

because (as discussed above) the overall rating may be influenced by an applicant's race. In this specification, the average marginal effect of Asian-American ethnicity becomes more negative, at -0.58, and remains statistically significant. The third row then removes Prof. Arcidiacono's interactions of race with other variables (such as disadvantaged status, gender, and missing variable indicators), and also removes interactions of gender with other variables (such as intended concentration), which for the reasons discussed above should not be included. In this specification, the average marginal effect of being Asian-American changes only slightly to -0.53 and remains statistically significant. Moving forward, when I refer to Prof. Arcidiacono's model, I will refer to the version in row 3, as that is the version that I will build on as I enrich the model.

133. The fourth row of Exhibit 17 reports the key results of my enriched model, where I begin with Prof. Arcidiacono's Model in row 3 and add in additional control variables detailed in Exhibit 14 above, including better measures of high school quality, high school and neighborhood demographics, socioeconomic status, and staff interview ratings.[110]

134. When I include these additional variables, the average estimated marginal effect of Asian-American ethnicity falls by over 70% to -0.14, and—crucially—it becomes *statistically insignificant* at the conventional 5% significance level. In other words, the model finds that there is *no statistically meaningful* effect of Asian-American ethnicity on applicants' likelihood of admission, controlling for all of the variables in my enriched model.[111]

135. Exhibit 18 shows in more detail how the average marginal effect of Asian-American ethnicity falls as I add additional controls to the pooled model. The addition of information on parental occupations causes the average marginal effect to fall from -0.59 to -0.41. Adding detailed high school and neighborhood information (on top of the parental occupation information) causes the effect to fall further to -0.29.[112] Further expanding the set of controls to include all the additional controls I use in my model (e.g. intended career, staff interview ratings, and an indicator of whether the applicant was born in the United States) causes the effect to fall still further, to -0.14, and to become insignificant. At each step, I test whether the variables I have added are jointly statistically

[110] Some variables in my model (but not Prof. Arcidiacono's model), such as the detailed College Board high school and neighborhood characteristics and the rural indicator, are unavailable for some applicants (primarily those on international dockets or those who are home-schooled). Thus, when I add these variables to the model, applicants missing this information are no longer included in the regression sample. Such applicants account for only 4.85% of the sample (see workpaper). Prof. Arcidiacono includes such applicants in his sample by assigning them all to the same high school and neighborhood clusters. This inappropriately groups applicants from varied backgrounds (such as those who are home-schooled in the United States and those attending international high schools) into the same cluster identifier.

[111] Treating Hawaiian/Pacific Islander applicants as Asian-American applicants attenuates the estimated effect even further to -0.09 (See workpaper).

[112] I reviewed the 60 individual high school and neighborhood variables available in the College Board data and found several were redundant (with one another or with information available in the Harvard database) or had other limitations that warranted their not being included.

significant, and in each case they are.

Exhibit 18

Additional control variables attenuate the estimated effect of Asian-American ethnicity

	Variables added	Average Marginal Effect of Asian-American Ethnicity	Additional Variables Jointly Significant
1.	Card pooled model without additional variables	-0.59 *	
2.	Adding parent occupation	-0.41 *	Yes
3.	Adding high school and neighborhood characteristics	-0.29 *	Yes
4.	Adding other variables	-0.14	Yes

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Data are from applicants in Professor Arcidiacono's corrected expanded sample. Marginal effects are calculated relative to White applicants. * indicates significance at the 5% level. Marginal effects are reported as percentage point values. Other variables include intended career, school type, parent attended Ivy League college, parent attended Harvard graduate school, parent living or deceased status, rural indicator, permanent resident indicator, and staff interview rating.

136. As detailed above in Sections 3 and 4, a fundamental problem with Prof. Arcidiacono's models is that they put a great deal of weight on academic variables by including both the academic rating *and* the various quantitative academic measures that inform that rating, but they include less information on the critical non-academic factors (including contextual factors like high school, neighborhood, and family background) that Harvard considers, and that differ on average between White and Asian-American applicants. As shown in the prior two exhibits, when I address this concern and include more variables that can capture differences across candidates in life experience and circumstance, the disparity between Asian-American and White admission rates is fully explained by the set of control variables in the model.

137. This result should not be surprising because a similar pattern is present (albeit to a lesser degree) in Prof. Arcidiacono's own models. Specifically, as he adds non-academic variables to his model, including measures of socioeconomic status and non-academic ratings, the alleged negative effect of Asian-American ethnicity is attenuated.[113] My enriched model has the same feature; it simply adds a more inclusive set of measures of such factors into the model.

138. This is still a pooled model, as opposed to the year-by-year models that I consider methodologically superior and that I discuss below. In other words, even if I accept Prof. Arcidiacono's methodological choice to use a pooled model, the addition of proper control variables

[113] Arcidiacono Report, Appendix B, Table B.7.2.

to his model negates any statistically significant negative effect of Asian-American ethnicity.

139. Before moving on, I want to respond to one additional argument Prof. Arcidiacono makes that is related to this point. Prof. Arcidiacono points to documents produced in this litigation from Harvard's Office of Institutional Research (OIR), summarizing statistical analyses performed by that office, as supposedly corroborating his findings and his methodology. A careful review of the relevant analyses, however, indicates that OIR's research methodology actually supports my methodological approach over Prof. Arcidiacono's. Specifically, the documents indicate that OIR understood that its models were "basic" and "preliminary" and that, like Prof. Arcidiacono's, they were missing important factors in the admissions process—particularly non-academic factors. For example, one of the documents states that "[t]here are a variety of factors that quantitative data is likely to miss or ratings not capture," and then lists as examples "[e]xceptional talent," "[t]he role of context cases," "[t]he role of the personal statement/essay," and "[m]easures of socioeconomic status."[114] In other words, OIR's documents recognize the same limitations in its analysis that I recognize in Prof. Arcidiacono's, and thus provide further support for my approach of expanding the set of control variables to help the model better control for the many non-academic factors that are important to the admissions process.

5.2.2. When the model is estimated year-by-year, it finds no evidence of a statistically significant negative effect of Asian-American ethnicity

140. As detailed in Section 5.1.2, in my opinion the correct way to model admissions decisions at Harvard is to examine each year separately. Prof. Arcidiacono's model does not do that; instead, it imposes the unrealistic assumption that Harvard's admissions process compares applicants across years and that each factor has the same effect in every year. The reality of the admissions process is quite different. Candidates compete only against the other candidates applying in that year, and Harvard's admissions decisions in each year depend on the specific set of applicants in the pool that year.[115] Moreover, as noted earlier, certain factors (like the use of Early Action) change from year to year.

141. In Exhibit 19, I report results for the year-by-year models, my preferred methodology. What I find is generally consistent with the pooled model. The average marginal effect of Asian-

[114] OIR Presentation at HARV00031722.

[115] A student who is admitted in a prior year but chooses to defer his admission, or a student offered deferred admission in a prior year, is considered part of the admitted class in the year for which he will enroll but is still compared, in the admissions process, only against other applicants in the year when he originally applied.

American ethnicity on applicants' likelihood of admission across all six years of data[116] is statistically indistinguishable from zero (-0.02), just like the average marginal effect in the pooled model, indicating no statistical evidence of bias.[117]

142. However, by estimating the model year-by-year, I also gain some important information. Specifically, in four of the six years the coefficients on Asian-American ethnicity are actually small and *positive*—in other words, Asian-American ethnicity (relative to White ethnicity) is associated with a *higher* likelihood of admission in those years, controlling for all other factors. The years with positive estimated effects include three of the four years since the reinstatement of Early Action with the class of 2016 cycle.[118]

[116] My pooled model generates a single estimate of the average marginal effect of Asian-American ethnicity on applicants' likelihood of admission. By contrast, my year-by-year model generates six different estimates—one for each class. To ensure that my year-by-year estimates are comparable with Prof. Arcidiacono's pooled estimate, I average the six year-by-year estimates to obtain an average effect across all six years of data. This approach allows me to use all the available years of data but estimate models that more accurately reflect Harvard's admissions process.

[117] This result also holds if I include average Advanced Placement exam scores in the 2017 – 2019 models (the only years for which they are available in the data). Prof. Arcidiacono excludes these from his pooled model analysis because they were only available in later years, but he argues that excluding such measures likely causes him to underestimate bias since these are measures on which Asian-American applicants are relatively strong (Arcidiacono Report, pp. 77–78). His dataset contains a variable for average AP exam scores for the classes of 2018 and 2019. I increase the coverage of this variable to include 2017 AP scores (which are stored in a different field) and include the expanded variable in my year-by-year models for 2017, 2018, and 2019. See workpaper.

[118] If I estimate this model treating Hawaiian/Pacific Islander applicants as Asian, the estimated effect becomes positive (though still statistically insignificant) on average across the six years. See workpaper.

Exhibit 19

Year-by-year logit models of admission show no consistent or statistically significant evidence of bias against Asian-American applicants

Class	Average Marginal Effect of Asian-American Ethnicity
1. **2014**	-0.41
2. **2015**	0.02
3. **2016**	0.12
4. **2017**	0.03
5. **2018**	-0.30
6. **2019**	0.36
Overall	-0.02

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Table shows the average marginal effect of race on admission for Asian-American applicants relative to White applicants using Professor Arcidiacono's corrected expanded sample. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

143. The predictive accuracy of my year-by-year enriched model is higher than that of *all* of Prof. Arcidiacono's models. As shown in Exhibit 20, my preferred model with the additional information correctly predicts the admissions outcome for 74% of applicants, while Prof. Arcidiacono's preferred model (Model 5) correctly predicts the outcome for only 67% of applicants.

Exhibit 20

Card model has higher predictive accuracy than Prof. Arcidiacono's preferred model

Model	Share of Admitted Applicants Correctly Predicted
1. **Professor Arcidiacono's model 5**	67%
2. **Adding personal rating and removing interactions**	71%
3. **Card pooled model**	72%
4. **Card by-year model**	74%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Table shows the total share of admitted students correctly predicted by the model. Card models use Professor Arcidiacono's corrected expanded sample; all other models use Professor Acidiacono's expanded sample. Predictions assume that the applicants are admitted in order of their predicted probability of admission from the model.

144. My model includes all applicants, including those who are waitlisted and then admitted or denied admission from the waitlist. Prof. Arcidiacono presents an analysis comparing the share of applicants of each race who were waitlisted and then denied admission to the admission rate of all applicants of each race. He suggests that the fact that Asian-American applicants are more likely to be denied admission after having been waitlisted, while having the lowest overall admission rate, reflects bias against Asian Americans.[119] That analysis is fundamentally incomplete and misleading, and cannot be taken as evidence of bias, because it does not account for the many qualifications that differ on average between Asian-American and White applicants. My admission model discussed above, which includes all applicants (including those who were waitlisted) and does account for differences in qualifications, finds no evidence of bias against Asian-American applicants.

5.2.3. Prof. Arcidiacono's analysis does not support the conclusion that the personal rating is biased

145. The models discussed above include as a control variable Harvard's personal rating. Using an ordered logit model that predicts personal ratings, Prof. Arcidiacono has argued that the personal rating is biased against Asian-American applicants. Based on this result, he then argues that the inclusion of the personal rating in the model is inappropriate. As discussed in Section 2 above, there are several reasons why Prof. Arcidiacono's statistical evidence of bias in the personal rating is weak and does not justify the exclusion of the personal rating from his model. Here, I expand on this issue.

146. First, Prof. Arcidiacono's model of personal ratings cannot reliably explain the

[119] Arcidiacono Report, pp. 31–32.

assignment of personal ratings. The Pseudo R-Squared value of the model is 0.28, which is quite low; for example, Prof. Arcidiacono's more reliable model of the academic rating has a Pseudo R-Squared value of 0.56.[120] Additionally the model has very low predictive accuracy. Of the 47 applicants in Prof. Arcidiacono's sample who have personal ratings of 1, his model correctly predicts their rating *zero* percent of the time, and of the 30,976 applicants with a rating of 2, it correctly predicts their rating only 45% of the time.[121]

147. As detailed above, a common methodological challenge in assessing the potential for racial bias using regression models is that a model almost always excludes some relevant information. This concern is particularly significant in attempting to model Harvard's personal rating, which considers many individualized and hard-to-quantify factors (i.e., the "missing data" I discuss above). Thus, if a regression estimates that race affects applicants' personal ratings, there is a serious question whether that estimated effect might actually be explained *not* by race but by racial differences in some factor that is not included in the model and that affects the personal rating—in other words, by omitted-variable bias (or "missing data"). One clear example of such missing data is an applicant's personal essay, which according to documents and testimony in this case is an important consideration in the determination of the personal rating.[122]

148. As discussed above, one way to determine if the missing data problem is affecting the estimated effects of race in a particular model is to consider how the estimated effect in the model changes as more of the available variables are added to the model. Importantly, Prof. Arcidiacono's own regression results show that the estimated effect of Asian-American ethnicity on the personal rating shrinks as non-academic factors are added to his model of the personal rating. This pattern suggests that, were more information available, the alleged effect could shrink further. For example, in Table B.6.7 of Prof. Arcidiacono's report, the coefficient of Asian-American ethnicity is -0.542 in Model 3 before he has added controls for neighborhood and school background and for the relevant ratings that feed into the personal rating. When he adds those controls (in his Model 5), the coefficient falls to -0.366.[123] If the model could account for unobserved factors like the personal

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[120] Arcidiacono Report, Appendix B, Table B.6.5 and Table B.6.7.

[121] See workpaper.

[122] See, for example, Banks Deposition, pp. 79–80 ("Q. And for each of those categories, can you tell me how they were assigned a numerical score?...[A] Extracurricularly, quality of achievement, strength of performance in any particular domain, personal qualities, some grasp of the candidate's personality, interest in other people, cooperation with others, a sense of responsibility as gleaned from teacher recommendations, personal interview, personal essay, et cetera. Q. Okay. So for the last category, the—the main inputs you would look at were recommendations, interview, and anything else? A. The candidate's essay."); Walsh Deposition, p. 60 ("Q. How would you calculate that score?…[A.] I would like to take into consideration whatever relevant information I had were that his essay, her essay, her interview, and the opinions about that applicant as expressed by others."); Ray Deposition, pp. 21–22 ("Q. What are the materials that you use—materials or considerations that go into determining this person's score?…A. For example, content in recommendation letters, personal essays.").

[123] Arcidiacono Report, Appendix B, Table B.6.7.

essay, the gap could fall further.

149. Another sign that Prof. Arcidiacono's regression models of the personal and overall ratings are not capturing actual bias against Asian-American applicants is that his models find a statistically significant *positive* effect of Asian-American ethnicity on the academic and extracurricular ratings. As noted above in Section 5.1.6, such a pattern calls into question whether the effects his models attribute to race are more properly explained by factors that are missing from his models (either because he does not include them or because they are unobservable). If Harvard were in fact biased against Asian-American applicants, it would make little sense for Harvard to give an unexplained advantage to Asian-American applicants in the academic and extracurricular ratings. On the other hand, if Harvard were *not* biased, but the ratings models were simply missing relevant variables that explain the differences across race in ratings assignments, it would not be surprising to see an inconsistent pattern of "bias" across the profile ratings.

150. Further, as detailed in Section 3, the essential function of the ratings is to quantify the otherwise unobservable information about applicants that admissions officers discern from their intensive review of each file. It is therefore unsurprising that regression models struggle to reliably explain the ratings; the whole point of the ratings is to capture information that is hard to measure.

151. Despite my view that Prof. Arcidiacono's analysis does not support an inference that the personal rating is biased against Asian-American applicants, I have also conducted an analysis that assumes for the sake of argument that the personal rating is biased, and therefore removes it from the model. This approach is an extremely conservative analysis that overcorrects for any concern of bias in the personal rating, because it completely removes from the model the personal rating (a factor on which White applicants, in aggregate, are relatively stronger than Asian-American applicants), rather than removing only the allegedly discriminatory component of the rating. In fact, Prof. Arcidiacono's Table 6.1—which uses his personal ratings regression to calculate the share of Asian-American applicants who would receive a rating of 1 or 2 under the assumption that there was no bias in the personal rating—shows that White applicants are still, on average, a bit more likely than Asian-American applicants to have a personal rating of 1 or 2.[124]

152. As Exhibit 21 shows, even in this very conservative model that ignores an important dimension of the admissions process on which White applicants are relatively strong, I still find only weak and inconsistent evidence of a disparity between Asian-American and White admission rates. Specifically, I find no evidence of a significant negative effect of Asian-American ethnicity in five of the six years of data I analyze.

[124] Arcidiacono Report, p. 57.

Exhibit 21

Logit model of admissions removing personal rating

Class	Average Marginal Effect of Asian-American Ethnicity
1. **2014**	-0.76
2. **2015**	-0.37
3. **2016**	-0.45
4. **2017**	0.05
5. **2018**	-0.68 *
6. **2019**	0.14
Overall	-0.34 *

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Table shows the average marginal effect of race on admission for Asian-American applicants relative to White applicants using Prof. Arcidiacono's corrected expanded sample. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

153. Additionally, Exhibit 22 shows the average marginal effect of Asian-American ethnicity if I remove the only class for which there is a statistically significant negative effect (the class of 2018) from my sensitivity analysis that excludes the personal rating. When I focus my analysis on the five admissions cycles other than 2018, the estimated effect of Asian-American ethnicity in each of those five years is statistically insignificant *and* the overall, average estimated effect across all five years becomes statistically insignificant (falling by 21% relative to the estimated effect over all six years). In other words, even if I exclude the personal rating from the model, there is no statistically significant gap in admissions between Asian-American applicants and White applicants outside of the 2018 admissions cycle.

Exhibit 22

Excluding 2018, logit model of admissions without personal rating shows no evidence of bias against Asian-American applicants

Class	Average Marginal Effect of Asian-American Ethnicity
1. **2014**	-0.76
2. **2015**	-0.37
3. **2016**	-0.45
4. **2017**	0.05
5. **2019**	0.14
Overall	-0.27

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Table shows the average marginal effect of race on admission for Asian-American applicants relative to White applicants using Prof. Arcidiacono's corrected expanded sample. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

154. Before moving on, I want to respond to three other arguments offered by Prof. Arcidiacono in support of his claim that the personal and overall ratings are biased. First, Prof. Arcidiacono's model of the overall rating, like his model of the personal rating and other non-academic ratings, is weak; it has a Pseudo R-Squared value of just 0.34.[125] Given the evidence detailed above that the estimated negative effect of Asian-American ethnicity on applicants' probability of admission shrinks as available non-academic qualifications are added to the model, and given that non-academic qualifications are harder to measure than academic qualifications, the small negative effect that the model attributes to Asian-American ethnicity is not reliable evidence of bias; it is entirely possible and even likely that that effect is attributable to omitted non-academic variables. Additionally, Prof. Arcidiacono's overall rating model has very poor predictive accuracy. Of the 109 applicants in Prof. Arcidiacono's sample who have overall ratings of 1 (including pluses and minuses), his model correctly predicts their rating only 18% of the time, and of the 8,124 applicants with a rating of 2 (including pluses and minuses), it correctly predicts their rating only 28% of the time.[126] Further, as explained above, I have not included the overall rating in any of my regressions because it is the one rating that may be influenced by applicants' race (in the sense that, for example, the overall ratings of African-American, Hispanic, or Other (AHO) applicants may reflect the contribution they would make to the racial diversity of the student body). As I have shown above, even without the overall rating in my regression, I find no evidence of systematic bias in Harvard's

[125] Arcidiacono Report, Appendix B, Table B.6.8.

[126] See workpaper.

admissions process against Asian-American applicants.

155. Second, Prof. Arcidiacono suggests that the school support (teacher and guidance counselor) ratings assigned by Harvard are biased against Asian-American applicants because he observes that Asian-American applicants with the strongest academic qualifications (defined as those in the top deciles (4-10) of the academic index) are less likely to receive strong school support ratings relative to applicants of other races.[127] Again, this conclusion depends on Prof. Arcidiacono's assumption that candidates who are strong on academic factors are also strong on non-academic factors—an assumption that, as discussed above, is not supported by the available data. The teacher and guidance counselor ratings reflect strength across both academic and non-academic dimensions. Thus, the small gap between Asian-American and White applicants' school support ratings may well be attributable to the fact that Asian-American applicants tend on average to be weaker than White applicants on the available measures of non-academic factors that Prof. Arcidiacono's analysis explicitly ignores by focusing on only deciles of the academic index.

156. Third, Prof. Arcidiacono also suggests that differences between the alumni overall and personal ratings and Harvard's admissions officers' overall and personal ratings show that Harvard's personal and overall ratings are biased. But that argument once again depends on Prof. Arcidiacono's regression models of the ratings—which, again, are quite low in predictive accuracy and do not reliably control for the many hard-to-measure factors that are likely very important to the determination of the ratings. Second, the alumni and admissions-officer ratings are based on different sources. An alumni personal rating reflects only the alumni interviewer's brief interaction with the applicant, whereas the personal rating assigned by Harvard admissions officers considers not just the alumni interview (to the extent it has occurred before the rating is assigned, which is often not the case) but also the candidate's essays, teacher recommendations, secondary school report, and so on. Alumni ratings are also much more generous in general. For example, 62% of applicants receive an alumni personal rating of 1 or 2, while only 23% of the sample receive a personal rating of 1 or 2.[128] Moreover, the personal ratings given by the Harvard admissions officers explain much more about Harvard's admissions decisions than the alumni interviewer personal ratings do. For Prof. Arcidiacono's expanded sample, the Pseudo R-Squared value of a model that controls for only the personal rating is 0.19, while a model that controls for only the alumni personal rating has a Pseudo R-Squared value of just 0.08.[129] Given all of this, it is not particularly surprising that there exist differences in the size of various coefficients across the two models.

[127] Arcidiacono Report, p. 48.

[128] See workpaper.

[129] See workpaper.

5.3. Analysis of key subgroups of the data further contradicts SFFA's claim of systematic bias

157. To further analyze SFFA's claim that Harvard's admissions process discriminates against Asian-American applicants, I have also examined how the estimated effect of Asian-American ethnicity differs across time periods and subgroups of the applicant pool.

158. As discussed above in Section 5.1.6, a common methodological challenge when using regression analysis to test for discrimination is that regressions typically cannot account for all relevant factors that differ between two groups of people—in this case, between Asian-American and White applicants. Further, as detailed in Sections 4 and 5 above, it is quite likely that both Prof. Arcidiacono's and my regression analyses do not fully account for the many non-academic factors that are critical to admissions decisions in Harvard's whole-person process (though my analysis accounts for such factors more fully than Prof. Arcidiacono's does). As a result, any gap that exists between Asian-American and White applicants (or any group of applicants) may in fact reflect average differences across race on factors not accounted for in the model.

159. One way to examine whether a racial disparity is attributable to bias is to assess whether it is robust and consistent across subgroups and time periods in the data. If discrimination against Asian-American applicants were the cause of the racial disparity in admission rates, one would expect to see a systematic and robust racial difference in admission rates across all relevant subgroups and time periods. By contrast, if the gap instead reflects differences across race in factors that Harvard considers when making admission decisions—but that are missing from the model—it is much more likely that the gap will vary across subgroups because, simply by chance, some subgroups in the data are likely to be particularly strong or weak, in aggregate, on factors not accounted for in the model.

160. In this section, I highlight a few patterns in the data that suggest the latter hypothesis is more plausible. Specifically, as I discuss below, I find that the alleged effect of Asian-American ethnicity is particularly small (and in fact positive rather than negative in most years—though statistically insignificant) for two very large subgroups of Asian-American applicants—female Asian-American applicants and Asian-American applicants applying from California dockets. I also discuss how the fluctuation in the effect of Asian-American ethnicity on admissions from year to year is inconsistent with the claim that Harvard's admissions process is biased.

5.3.1. Asian-American ethnicity is associated with, if anything, a higher likelihood of admission for female applicants

161. When my model is estimated only on female applicants, Asian-American ethnicity is

associated with a slightly *higher* probability of admission (though the difference is not statistically significant). Exhibit 23 shows the results of my model for just the female sample. The effect of Asian-American ethnicity is positive in five of six years and overall (and insignificant across the board).

Exhibit 23

Average marginal effect of Asian-American ethnicity on admission is insignificant for Asian-American women

Class	Average Marginal Effect of Asian-American Ethnicity, Women Only
1. **2014**	0.26
2. **2015**	0.49
3. **2016**	0.06
4. **2017**	0.05
5. **2018**	-0.19
6. **2019**	0.34
Overall	0.17

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Table shows the average marginal effect of race on admission, for Asian-American applicants relative to White applicants, using Professor Arcidiacono's corrected expanded sample. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

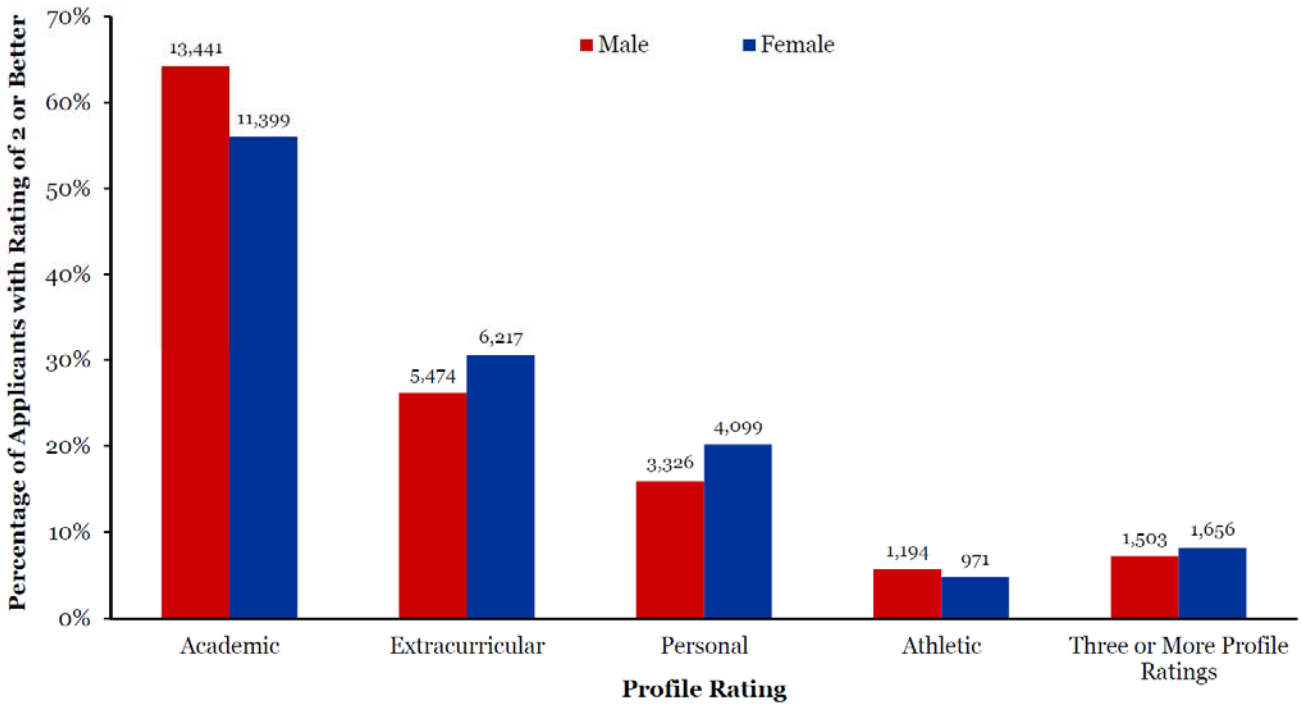
162. This pattern is particularly interesting because Asian-American women are stronger on non-academic dimensions than Asian-American applicants as a whole. Exhibit 24 shows that while Asian-American men are stronger than Asian-American women on the academic rating, Asian-American women are stronger on two of the three non-academic ratings, including the personal rating. Additionally, Asian-American women are more likely to be multi-dimensional (i.e. have three or more ratings of 2 or better) than Asian-American men. In other words, Asian-American women are a bit less strong on academics than Asian-American men, but make up for it by being relatively stronger on other dimensions.

163. The fact that Asian-American female applicants are stronger on non-academic factors than Asian-American male applicants, are more multi-dimensional than Asian-American male applicants, *and*, if anything, may have a small *advantage* over White female applicants is consistent with my interpretation that any unexplained gap between Asian-American and White applicants in

the models is in fact driven by average differences in unmeasured non-academic factors, rather than by discrimination against Asian-American applicants.

Exhibit 24

Asian-American female applicants are stronger on non-academic measures and more multi-dimensional than Asian-American male applicants



Source: Arcidiacono Data

Note: Data are from Asian-American applicants to the classes of 2014 – 2019 in Professor Arcidiacono's corrected expanded sample. Ratings of 2- and above are classified as "2 or better" in this analysis. +/- rating designations are available in the data beginning with the class of 2019.

5.3.2. Asian-American ethnicity is associated with a higher likelihood of admission for applicants on California dockets

164. I also find that Asian-American ethnicity is associated with a slightly (though not statistically significantly) higher probability of admission for applicants on California dockets —a useful focal point for analysis because nearly 30% of Asian-American applicants are on California dockets.

165. If Harvard's admissions process sought to limit the number of Asian-American applicants, it would be unlikely to favor Asian-American applicants relative to White applicants in the region in which Asian-American applicants are most concentrated. Yet, when I estimate my logit

model on applicants from California dockets only, I find that Asian-American applicants are, if anything, slightly more likely to be admitted than White applicants with the same observable characteristics. This result does not suggest that Harvard is biased in favor of Asian-American applicants on California dockets; it suggests, instead, that any perceived negative effect of Asian-American ethnicity in the national pool is more likely explained by factors omitted from the model that vary across regions.

Exhibit 25

Admission rates for Asian-American applicants on California dockets are, if anything, higher than those of White applicants once available factors are controlled for

Class	Average Marginal Effect of Asian-American Ethnicity
1. **2014**	-0.22
2. **2015**	0.57
3. **2016**	0.54
4. **2017**	0.36
5. **2018**	0.13
6. **2019**	0.43
Overall	0.31

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the classes of 2014 – 2019 in Professor Arcidiacono's corrected expanded sample who are applying from California dockets. Average marginal effects are calculated from the Card Model. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

166. Exhibit 25 presents the estimated marginal effect of Asian-American ethnicity for applicants on California dockets. That effect is positive in five of six years and overall (and insignificant in all years). These findings provide further evidence that Harvard's admissions process exhibits no evidence of systematic discrimination against Asian-American applicants relative to White applicants.

5.3.3. Evidence of the alleged disparity is also inconsistent across years

167. As noted above, my admissions model also exhibits year-by-year variation in the estimated effect of Asian-American ethnicity on applicants' likelihood of admission. For example, in my preferred specification, the estimated effect of Asian-American ethnicity is negative in some years and positive in others, with four of the six years exhibiting a *positive* (albeit still statistically

insignificant) association between Asian-American ethnicity and applicants' likelihood of admission, and two of the six years a negative (albeit still statistically insignificant) association.

168. Even in my sensitivity analysis in which I exclude the personal rating from the model, the estimated effect of Asian-American ethnicity is not consistent from year to year. As noted above, the estimated effect of Asian-American ethnicity is statistically significant only in the class of 2018 admissions cycle, and when that cycle is excluded, the *average* estimated effect across the other five years is not statistically significant. Additionally, the estimated effect of Asian-American ethnicity changes from positive to negative between years, with two of the six years being positive in this model.

169. If Harvard's admissions process were biased against Asian-American applicants throughout this whole time period (as SFFA alleges), one would expect see a more consistent pattern from year to year. The fact that the alleged "bias" fluctuates above and below zero from year to year is more consistent with applicant pools from different years having a slightly different mix of unmeasured, non-academic factors across ethnic groups that the model cannot perfectly account for, than it is with the allegation of systematic bias against Asian-American applicants.

5.4. Conclusion

170. In this section, I have developed a statistical model that improves Prof. Arcidiacono's model by including in it a wide variety of factors that Harvard considers when making admissions decisions and that Prof. Arcidiacono did not include in his model. My model also more accurately reflects Harvard's yearly admissions process in which applicants are compared only to other applicants applying in the same year and not to applicants applying in other years.

171. I find no evidence of systematic bias against Asian-American applicants relative to White applicants, after controlling for the many differences between these groups. While Asian-American applicants tend to have stronger academic qualifications, White applicants tend to be stronger on non-academic dimensions. Prof. Arcidiacono's model places a great deal of weight on academic qualifications (including both the academic rating and the academic factors that inform that rating), while omitting information related to each candidate's life circumstances, including detailed variables describing each high school and neighborhood in the data. When I add such measures to the model to better account for the differences across all dimensions that Harvard considers (and for which I have data), I find no statistically significant negative effect of Asian-American ethnicity relative to White ethnicity on applicants' probability of admission. Furthermore, the estimated effect of Asian-American ethnicity relative to White ethnicity is positive in four of the six years.

172. I also estimate a version of my model that assumes, as Prof. Arcidiacono alleges, that the personal rating is biased against Asian-American applicants. I show that, even if the personal rating is completely excluded from the model, there is at most weak evidence of a negative effect of Asian-American ethnicity on applicants' likelihood of admission. In any event, Prof. Arcidiacono's findings of bias in the personal rating are weak for several reasons. His models of the various ratings (aside from the academic rating) have low explanatory power. Additionally, he finds a *significant and positive* effect of Asian-American ethnicity on two of the four profile ratings, which casts doubt on whether the results actually reveal racial bias rather than simply the effect of unobservable factors that differ across race. Collectively, the results of Prof. Arcidiacono's ratings regressions are more consistent with the absence of relevant difficult-to-quantify information from the database (or from Prof. Arcidiacono's models) than with systematic bias against Asian-American applicants.

173. Finally, I find that the alleged disparity between Asian-American and White admission rates is inconsistent from subgroup to subgroup and from year to year. I find particularly weak evidence of bias against female Asian-American applicants and Asian-American applicants on California dockets. If anything, Asian-American applicants in those two groups are admitted at slightly higher rates than comparable White applicants, controlling for relevant factors. Since 30% of Asian-American applicants are on California dockets, and half are female, it is hard to reconcile those findings with SFFA's claim that Harvard intentionally and systematically discriminates against Asian-American applicants on the basis of their race. I also find that the effect of Asian-American ethnicity fluctuates from year to year, and is positive in four of six years. I am not aware of any basis to believe that Harvard's process was somehow biased in some years but not others. Again, these results—taken together—suggest that any estimate of a negative effect of Asian-American ethnicity at the national level reflects not racial discrimination but rather the effect of factors that are omitted from the model because they cannot be quantified, and that vary across genders, regions, and years.

6. AVAILABLE DATA DO NOT INDICATE THAT RACE IS A DETERMINATIVE FACTOR IN ADMISSIONS AT HARVARD

174. In this section, I turn to a different research question regarding the importance of race in Harvard's admissions process. Using the regression model developed in Section 5 above, I explore the size of the estimated effect of an applicant's race or ethnicity on her likelihood of admission, relative to the effect of the many other factors Harvard considers in its whole-person analysis.

175. Exhibit 26 summarizes the estimated average marginal effect of each racial category on an applicant's likelihood of admission. As already discussed in Section 5 above, the estimated effect of Asian-American ethnicity is statistically indistinguishable from zero in every year. The estimated effect of African-American ethnicity ranges from 5.20 percentage points to 7.43 percentage points, and averages 6.12 percentage points, while the estimated effect of Hispanic and Other races (such as Native American, and Hawaiian/Pacific Islander) ranges from 3.12 percentage points to 4.16 percentage points, and averages 3.73 percentage points.

Exhibit 26

Average marginal effect of race on the probability of admission

Class	Asian-American	African-American	Hispanic and Other	Missing
1. **2014**	-0.41	7.43 *	3.81 *	0.39
2. **2015**	0.02	6.47 *	4.04 *	0.42
3. **2016**	0.12	5.20 *	3.17 *	-0.26
4. **2017**	0.03	5.85 *	4.16 *	-0.06
5. **2018**	-0.30	6.19 *	4.13 *	-0.01
6. **2019**	0.36	5.78 *	3.12 *	-0.30
Overall	-0.02	6.12 *	3.73 *	-0.08

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Tables shows the estimated average marginal effect of race on admission, for each listed race, using Professor Arcidiacono's corrected expanded sample. * indicates significance at the 5% level. Marginal effects are reported in percentage point values.

176. In the remainder of this section, I offer a variety of analyses that provide context for how important or unimportant race is relative to other factors in the admissions process. I find that (a) the importance of race in explaining admissions decisions is substantially smaller than that of other key factors Harvard considers; (b) even when race plays a role in admissions decisions, other applicant attributes play a significant role as well; and (c) the effect of race is smaller than that of individualized, unmeasured factors that are independent of race. All of these facts indicate that,

although race plays a role in admissions decisions, it is only one of a variety of factors considered and is not the determinative factor.

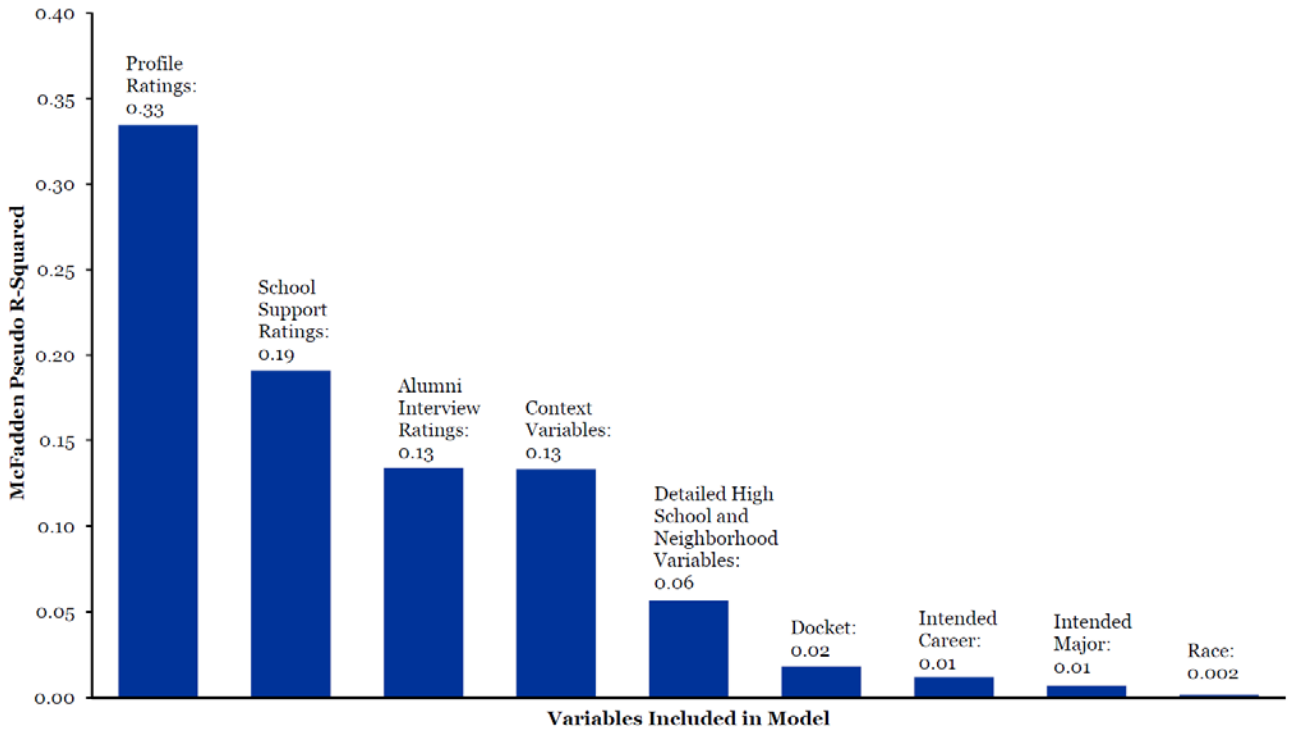
6.1. Race is less important than other factors in admissions decisions

177. A starting point for estimating the effect of race relative to other factors in the admissions process is to compare how effectively race explains admissions outcomes, relative to other important factors Harvard considers in admissions. If race were a determinative factor, then knowing an applicant's race would allow one to predict with a high degree of certainty whether or not the applicant is admitted.

178. Exhibit 27 reports the Pseudo R-Squared value for regressions of admissions outcomes for the class of 2019 that include *only* racial categories as control variables, as well as regressions that include only control variables *other* than race. As discussed above, Pseudo R-Squared is a statistic that captures how well a variable (or set of variables) can explain admission decisions. It takes on values from zero to one and is meant to approximate the share of the variation in actual admission decisions that can be explained by the variables in the model. As shown in Exhibit 27, a regression that includes only the variables for racial categories has a tiny Pseudo R-Squared value—just 0.002. That means that race alone explains almost nothing about admissions outcomes. For comparison's sake, the profile ratings collectively explain a much larger proportion of the variability in admissions outcomes (Pseudo R-Squared value of 0.33). School support ratings and alumni interview ratings have Pseudo R-Squared values of 0.19 and 0.13, respectively. Even contextual factors that I include in my model but that Prof. Arcidiacono does not include in his—such as College Board high school and neighborhood variables, parental occupation, and intended career—explain more about admissions decisions than race.

Exhibit 27

Many factors better explain admission decisions than race



Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Data are from applicants to the class of 2019 in Professor Arcidiacono's corrected expanded sample.

179. In Table 7.1 of his report, Prof. Arcidiacono shows that, according to his model, many Asian-American applicants with a 25% estimated likelihood of admission would have an estimated likelihood of admission of over 90% if they were African-American.[130] That is a misleading and incomplete way to measure the relative importance of race for at least two reasons.

180. First, Prof. Arcidiacono has misleadingly selected a particular combination of applicant characteristics for which the effect of race is largest. Exhibit 28 provides a fuller analysis that examines the effect of race across *all* applicants, rather than a single example. It shows the average estimated effect of race on probability of admission for African-American and Hispanic and Other applicants (relative to White applicants) according to my year-by-year model *for each decile* of the admissions index—a metric Prof. Arcidiacono has used in his analysis that measures the predicted probability of admission absent consideration of race. As is clear, the higher likelihood of admission associated with African-American ethnicity averages 13 percentage points or less for applicants in the first nine deciles (that is, 90% of African-American applicants). For applicants in the highest decile

[130] Arcidiacono Report, pp. 65–66.

(the strongest applicants), it averages 47 percentage points. For applicants of Hispanic or Other (non-Asian) minority race, the estimated effect of race averages seven percentage points or less for applicants in the first nine deciles and 29 percentage points for applicants in the highest decile.

Exhibit 28

Average marginal effect of race is small for the vast majority of AHO applicants

Predicted Probability of Admission Decile	Average Marginal Effect	
	African-American Applicants	Hispanic or Other Applicants
1. **1 (Weakest)**	0.00	0.00
2. **2**	0.00	0.00
3. **3**	0.00	0.00
4. **4**	0.00	0.00
5. **5**	0.00	0.01
6. **6**	0.02	0.05
7. **7**	0.18	0.22
8. **8**	1.24	1.08
9. **9**	12.65	7.05
10. **10 (Strongest)**	47.08	28.85

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the classes of 2014 – 2019 in Professor Arcidiacono's corrected expanded sample. Deciles are constructed by race based on the predicted probabilities of admission when the race factor is turned off. Marginal effects are calculated relative to White applicants using Card year-by-year admissions model. Marginal effects are reported as percentage point values.

181. Second, the applicants with the largest estimated positive effect of race on their likelihood of admission are the strongest applicants—i.e., those whose estimated likelihood of admission is in the top 10% of the applicant pool absent consideration of race. Race is not a "determinative" factor for such applicants, even if it has a significant positive effect on their likelihood of admission, because they are strong in other respects. One way to see this fact is that 77% of AHO admitted students have at least two profile ratings of 2 or better.[131] Applicants with at least two profile ratings of 2 or better already have an admission rate of 23%.[132]

[131] See workpaper.

[132] See workpaper.

6.2. Race is less important than unmeasured, individualized factors

182. It is also possible to compare the effect of race in Harvard's admissions process to that of individualized, unmeasured factors—that is, factors not captured by the model. One way to do that is to examine the predicted probability of admission for each applicant and compare that to the actual admission decision for the applicant.

183. As discussed in Section 5.1.6 above, if the model generates a predicted probability of admission close to zero for a candidate who was rejected or a predicted probability of admission close to one for a candidate who was admitted, one can conclude that the variables in the model allow the researcher to be very confident about that applicant's admissions outcome. If, however, the model generates a predicted probability of admission of, say, 0.10 for a given candidate who was actually admitted, one can conclude that the variables in the model do not allow the researcher to explain with any degree of certainty why the applicant was admitted. In other words, it is the *unquantifiable* factors that ultimately determined whether the candidate was admitted. More generally, one can quantify the importance of such factors by using the "error" term from the model—that is, the actual admission outcome (1=admitted) minus the estimated admission outcome (0.10)—which measures the relative importance of factors specific to that individual that are not included in the model.

184. To give a concrete example, consider an applicant who is not admitted and whose SAT scores and GPA are so low that it is essentially impossible for the applicant to be admitted. For such an applicant, one can conclude that unquantified factors not present in the model are not a major factor in the decision—the observable information on academic achievements is sufficient to understand the decision. The applicant's estimated likelihood of admission will be close to zero, and the applicant's actual admissions outcome will be zero (not admitted), so the error term will be very small. On the other hand, consider an applicant with an academic rating of 3, an extracurricular rating of 2, and a personal rating of 2. Suppose the model predicts the applicant has a 40% chance of admission, and ultimately she is in fact admitted. What I conclude from such information is that other factors that are specific to that candidate that are *not* observed in the model explain 60% of the outcome—the difference between the applicant's actual likelihood of admission (100%) and her estimated likelihood of admission according to the model (40%).

185. By comparing the marginal effect of race for any given applicant to the error in the model, it is possible to compare the role of race in the admissions process to the role played by unobserved factors that are independent of race. Exhibit 29 shows that the portion of the admissions decision attributable to unobserved characteristics of each individual applicant is *greater than* the effect of race for 100% of Asian-American applicants, for 94% of African-American applicants, and for 96% of Hispanic or Other applicants. In other words, in nearly all cases, race matters less to an

applicant's admissions outcome than individualized factors that are not in the model.

Exhibit 29

Average marginal effect of race is small compared to importance of unobserved characteristics

Race	Mean Absolute Deviation	Average Marginal Effect of Race Including Perfect Predictions	Fraction of Race With Absolute Deviation Greater Than Or Equal To Absolute Value of Marginal Effect
1. **Asian-American**	5.11	-0.02	100%
2. **Hispanic or Other**	5.40	3.73	96%
3. **African-American**	5.57	6.12	94%
4. **Race Missing**	5.51	-0.08	100%

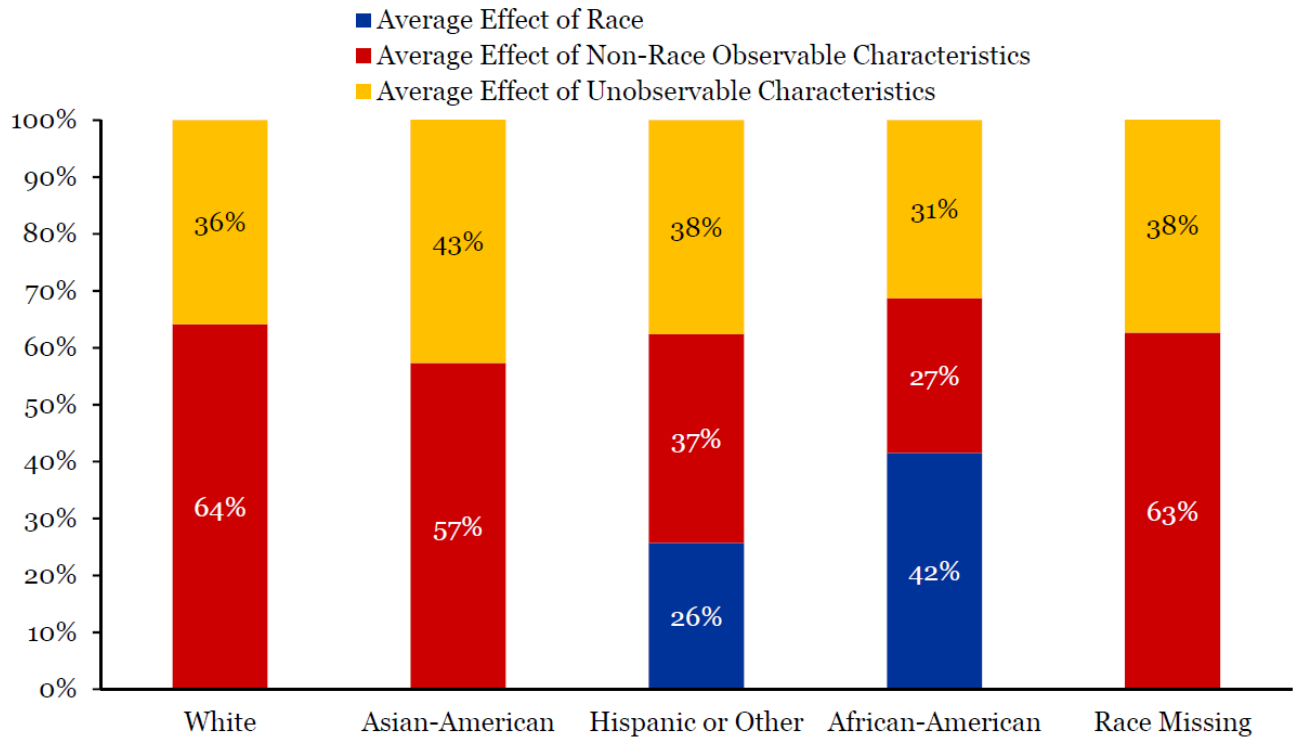
Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Data are from applicants to the classes of 2014 – 2019 in Prof. Arcidiacono's corrected expanded sample. Absolute deviations and marginal effects are reported as percentage point values. Table shows the average marginal effect of race on admission relative to White applicants. Absolute deviation is computed by taking the absolute value of the difference between the actual admitted status and the predicted probability of each applicant. Absolute deviation is compared with the absolute value of the marginal effect for each applicant.

186. Exhibit 30 shows the effect of race relative to other observed and unobserved factors focusing only on applicants who were admitted to Harvard. Each bar shows the relative effect of three different groups of factors in the model: race, observable factors other than race, and unobservable factors that are specific to individuals and not captured in the model. Even for African-American admitted students, race explains less than half (42%) of the variability in admissions outcomes. For Hispanic or Other minority race applicants, race explains only 26% of the variability in admissions outcomes. In other words, non-race factors play a large role.

Exhibit 30

Non-racial factors play the dominant role in admissions decisions



Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Data are from students admitted to the classes of 2014 – 2019 in Prof. Arcidiacono's corrected expanded sample. Average effect of race is computed as the average marginal effect of race on admission relative to White applicants. Average effect of non-race observable characteristics is computed as the average difference between the predicted probability and the marginal effect of race. Average effect of unobservable characteristics is computed as the mean absolute deviation. Absolute deviation is computed by taking the absolute value of the difference between the actual admitted status (0 or 1) and the predicted probability of admission for each applicant.

6.3. Prof. Arcidiacono's claim about a "floor" for the admission rate of African-American applicants is not supported by available data

187. Prof. Arcidiacono also asserts that, starting with the class of 2017, Harvard intentionally sought to match the admission rate for African-American applicants to the admission rate for all applicants. That assertion is not supported by available data.

188. Prof. Arcidiacono claims that the impetus for this practice was that, beginning with the class of 2017, "Harvard adopted a new methodology for coding race and ethnicity that was consistent with federal standards for reporting of race and ethnicity."[133] Under that methodology—known as the Integrated Postsecondary Education Data System (IPEDS) methodology—students who identify as

[133] Arcidiacono Report, p. 27.

African-American and another race are counted as "multiracial," not as African-American. The IPEDS methodology contrasts with Harvard's historical method for classifying race (the "Old Methodology"), which categorizes any applicant who identifies as African-American as African-American, whether or not that applicant also identifies with another racial or ethnic group. It also contrasts with Harvard's current preferred method for classifying race (the "New Methodology"), which counts applicants in as many racial categories as they choose to identify on their applications (so that an applicant who identified as African-American and, say, Asian-American would be counted in both categories). Professor Arcidiacono argues that the IPEDS methodology "prompted concern at Harvard that the new reporting would understate the number of African-American admits to Harvard."[134] He argues that this concern drove Harvard to impose a floor on the African-American admission rate.

189. In this section I consider both the substance of Prof. Arcidiacono's claim, as well as whether the data are consistent more broadly with the idea that Harvard is imposing a floor on the admission rate for African-American applicants.

190. As an initial matter, Prof. Arcidiacono does not explain why Harvard would care about manipulating the admission rate of candidates who are African-American according to the IPEDS methodology. First, Harvard does not publicly release admission rates by race, so it is unclear why Harvard would be sensitive to the public perception of its admission rates by race.[135] Second, when Harvard publicly announces the racial composition of the admitted and matriculating classes (as opposed to the admission rates), it does so using its *own* definitions of race—first the "Old Methodology" (used since at least the class of 1980) and now the "New Methodology" discussed above. Harvard does not publicly report racial statistics using the IPEDS methodology.[136] Finally, the IPEDS methodology was not new in the class of 2017 admissions cycle; in accordance with federal reporting requirements, Harvard had already been reporting race to the government using the IPEDS

[134] Arcidiacono Report, p. 28.

[135] Fitzsimmons Deposition, pp. 453–454 ("Q. Does Harvard publicly report its admission rate by ethnicity? A. No.").

[136] Yong Deposition, p. 138 ("Q. But you don't use the IPEDS methodology? A. Not for press releases."); Fitzsimmons Deposition, pp. 100–101 ("Q. When Harvard reports its results in the Harvard Gazette, does it use the IPEDS methodology or the new methodology to describe the ethnic characteristics of the class? A. It would use the new methodology."); Table, Aggregate applicant data 1980 – 2018, HARV00023177 – 8.

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methodology since the 2010–11 school year (entering class of 2014), three years earlier.[137]

191. Furthermore, Prof. Arcidiacono's selective focus on the admission rate as defined using the IPEDS methodology presumably reflects the fact that admission rates calculated using Harvard's own preferred methodologies *do not* show the effect he regards as problematic—in other words, the admission rate for African-American candidates (as defined using the New Methodology and Old Methodology) does not match the overall admission rate. For example, for the class of 2016, the African-American admission rate based on both the "New Methodology" and the "Old Methodology" was nearly a half point *below* the admission rate of all other applicants.[138]

192. In addition, if Harvard had lowered its admission standards to ensure an artificially high admission rate for African-American applicants, one might expect to see a decline in the relative quality of African-American admitted students starting in the class of 2017. No such decline occurred.[139] Further, the estimated positive effect of African-American ethnicity on applicants' likelihood of admission (based on my regression analysis in Exhibit 26) is generally *smaller* for applicants to the classes of 2017 to 2019 than for applicants to the classes of 2014 and 2015. If Harvard implemented a floor for the admission rate of African-American students starting with the class of 2017, the regression model should show a *larger* positive association between African-American ethnicity and likelihood of admission in later years than in prior years—not a smaller one.

193. Finally, Harvard has produced aggregate admission data by race, using its Old Methodology, that extend back to 2000. Using that aggregate data I can examine the fluctuations from year to year in admissions decisions by race, and assess whether such fluctuations are in any way consistent with a "floor" in admissions for African-American applicants, and/or a substantive change starting with the class of 2017.

194. Exhibit 31 through Exhibit 34 report the year-to-year fluctuations in the racial composition of the admitted class. There is no evidence that Harvard has sought to achieve a consistent proportion of African-American students. To the contrary, the share of admitted students who are African-American fluctuates considerably from year to year, by as much as 14%. Similar patterns exist for all races. For example, despite SFFA's claims that Harvard seeks to limit the share of its class that is Asian-American, Exhibit 32 shows that the share of the class that is Asian-American has fluctuated significantly.

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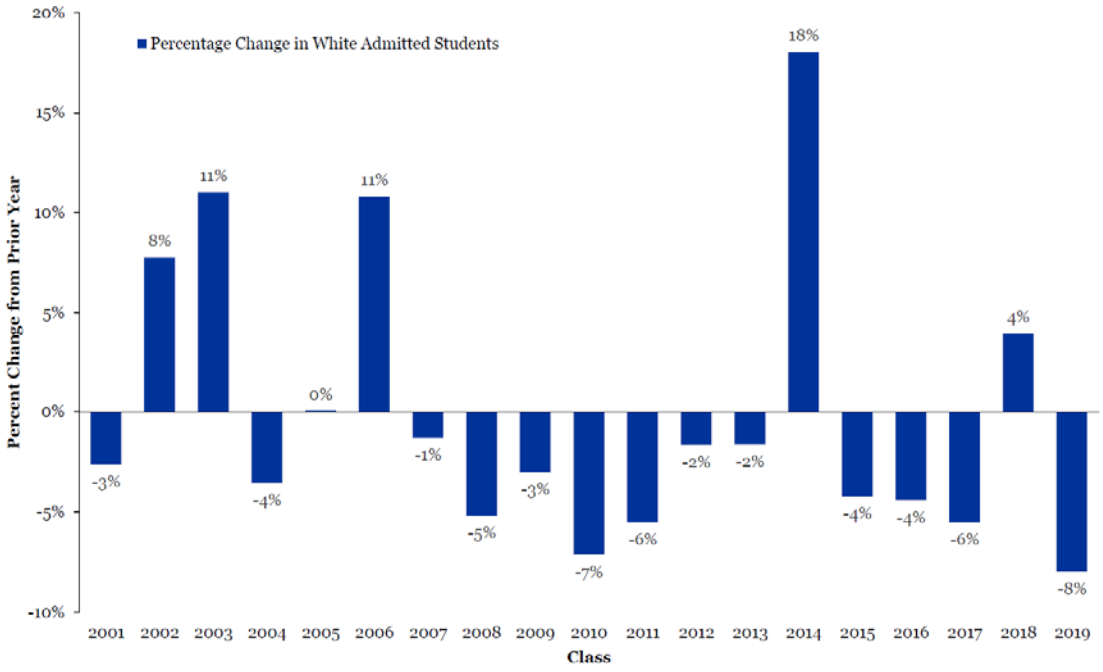
[137] Harvard Memo, "A Note on the Collection and Reporting of Data on Race and Ethnicity," HARV00065450 – 52 at HARV00065450 – 51; "Resources for Implementing Changes to Race/Ethnicity Reporting in IPEDS," *National Center for Education Statistics*, available at https://nces.ed.gov/ipeds/Section/Resources, accessed December 1, 2017.

[138] See workpaper.

[139] See workpaper.

Exhibit 31

The fraction of admitted students who are White fluctuates over time

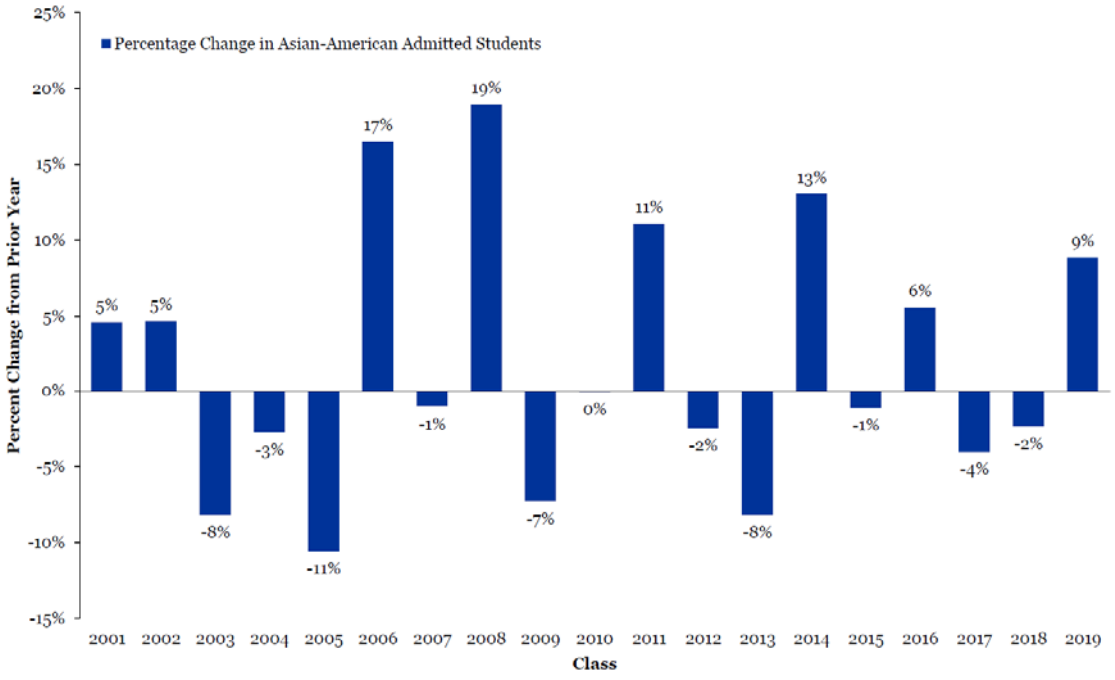


Source: HARV00001848 – 1850; Augmented Arcidiacono Data

Note: Sample consists of domestic applicants who are classified as White under the Old Methodology.

Exhibit 32

The fraction of admitted students who are Asian-American fluctuates over time

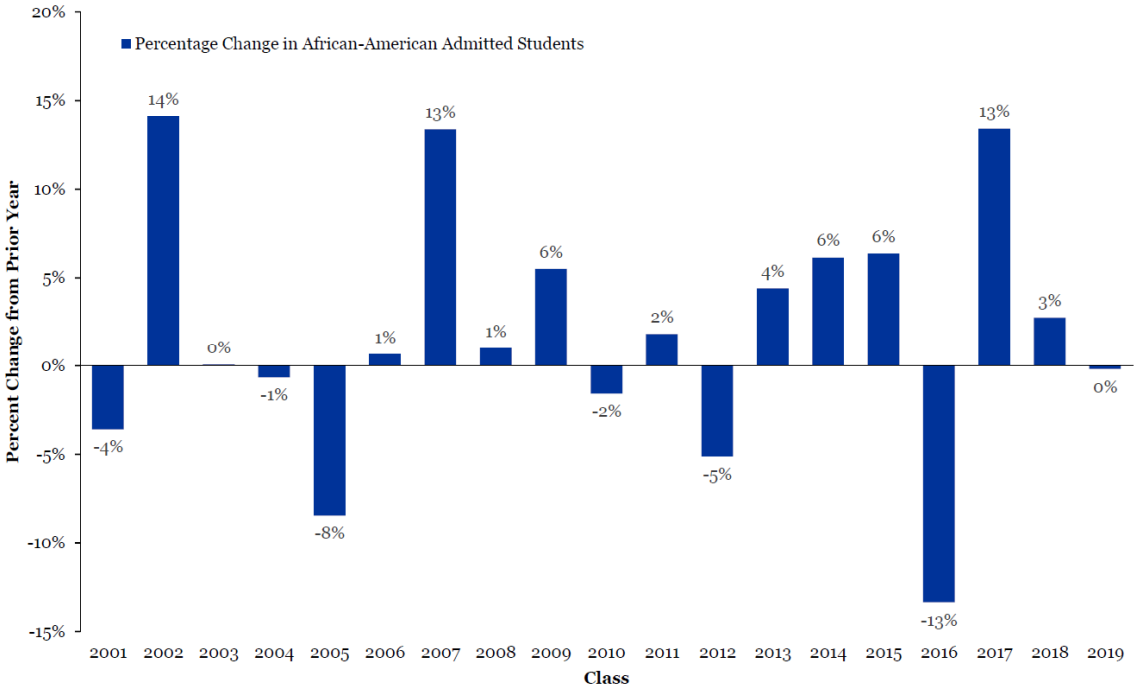


Source: HARV00001848 – 1850; Augmented Arcidiacono Data

Note: Sample consists of domestic applicants who are classified as Asian-American under the Old Methodology.

Exhibit 33

The fraction of admitted students who are African-American fluctuates over time

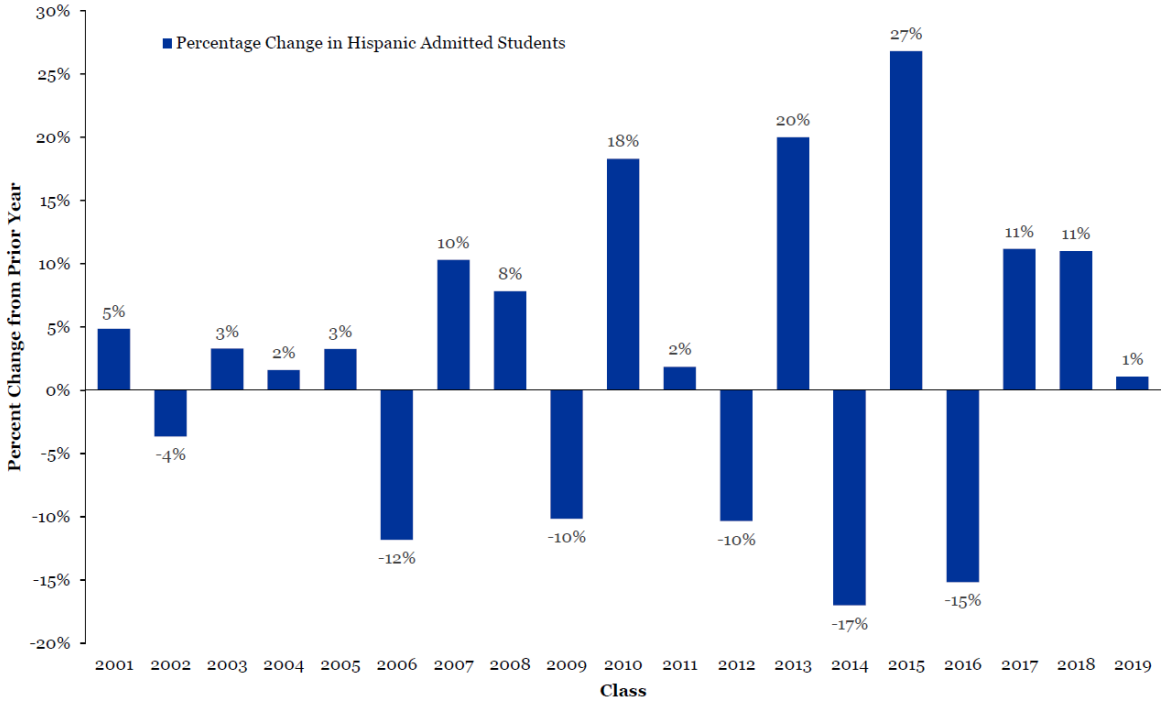


Source: HARV00001848 – 1850; Augmented Arcidiacono Data

Note: Sample consists of domestic applicants who are classified as African-American under the Old Methodology.

Exhibit 34

The fraction of admitted students who are Hispanic or Other fluctuates over time



Source: HARV00001848 – 1850; Augmented Arcidiacono Data

Note: Sample consists of domestic applicants who are classified as Hispanic or Other under the Old Methodology.

6.4. Conclusion

195. As detailed above, I find little evidence that race is a determinative factor in the admissions process. Specifically, I find that race explains much less about applicants' likelihood of admission than numerous other factors Harvard considers.

196. I also examine Prof. Arcidiacono's claim that the marginal effect of race can be quite large for certain individual candidates. I find that the marginal effect of race averages 13 percentage points or less for 90% of African-American applicants and averages 7 percentage points or less for 90% of Hispanic or Other applicants. And for the small number of applicants for whom race plays a more significant role, other non-race factors also substantially affect the applicants' likelihood of admission. Further, I find that the average marginal effect of race is less than that of individualized, unmeasured factors that are independent of race. For admitted AHO applicants in particular, race explains only about 34% of the variation in admissions outcomes.[140]

[140] See workpaper.

197. Finally, I also consider Prof. Arcidiacono's claim that Harvard began manipulating its admission rate for African-American applicants—as defined using the IPEDS methodology—starting with the class of 2017 admissions cycle. It is highly implausible that Harvard would attempt to manipulate that particular statistic, which it does not release to the public. And, indeed, a review of the data using Harvard's preferred methods for categorizing applicants by race does not show the effect Prof. Arcidiacono observes.

7. ANALYSIS OF POTENTIAL RACE-NEUTRAL ALTERNATIVES

198. In this section, I address the question of how the racial composition and other attributes of Harvard's admitted class would be expected to change if Harvard stopped considering race and instead pursued a variety of race-neutral ways of seeking to increase the racial diversity of its admitted class. My findings indicate that, to the extent race-neutral practices can enable Harvard to achieve racial diversity, they would do so only by altering other characteristics of the admitted class that I understand matter to Harvard.

199. I begin by surveying the academic literature on race-neutral alternatives—including papers suggested by SFFA and its expert, Richard Kahlenberg—in order to identify admissions practices that have been posited to be effective at increasing racial diversity. I also discuss the literature evaluating these practices and whether they could work at a highly selective university like Harvard. Next, I use Harvard's admissions data to demonstrate how various potential race-neutral admissions practices would be expected to affect the racial composition and other attributes of Harvard's admitted class. Finally, I discuss Mr. Kahlenberg's analysis of race-neutral alternatives.

200. I reach several conclusions. First, Harvard already engages in extensive race-neutral efforts to increase the racial diversity of its student body. Second, consistent with the academic literature, I find that Harvard's use of additional race-neutral efforts to increase racial diversity would not likely enable it to achieve a comparably diverse class if it did not consider race in admissions. To the extent that the use of race-neutral alternatives did enable Harvard to achieve a comparably diverse class, it would likely have a substantial deleterious effect on the quality of the admitted class along many dimensions. Finally, I find that Mr. Kahlenberg's proposed race-neutral alternatives do not depart from this pattern—that is, they either are ineffective at generating a racially diverse class, or would significantly alter the composition of the admitted class along other dimensions.

7.1. Race-neutral alternatives identified in academic literature and by SFFA

201. To develop a comprehensive list of race-neutral alternatives that Harvard could consider, I first considered the race-neutral alternatives identified by SFFA and its expert, Mr. Kahlenberg, then explored the academic literature for additional race-neutral alternatives that SFFA potentially overlooked. In this section, I summarize the race-neutral alternatives I found.

7.1.1. Race-neutral alternatives identified by SFFA and its expert

202. In Section X of the Complaint and in the Kahlenberg Report, SFFA and Mr. Kahlenberg list a series of race-neutral alternatives that have been identified in academic literature, and that they

believe would allow Harvard to achieve racial diversity without considering race.

203. First, SFFA and Mr. Kahlenberg suggest that Harvard should eliminate admissions practices that supposedly diminish racial diversity—namely (1) the consideration of whether an applicant's parents attended Harvard or Radcliffe (i.e., whether the applicant is a "lineage applicant"), (2) the consideration of whether an applicant's parents are members of Harvard's faculty or staff, (3) the practice of offering applicants deferred admission to a class subsequent to the one for which they applied, (4) the alleged consideration of whether an applicant's family has contributed or has the ability to contribute financially to Harvard, (5) the practice of tracking the admissions status of candidates of particular interest to Harvard's Dean and Director of Admissions, and (6) the practice of Early Action admissions. Mr. Kahlenberg also suggests that removing consideration for recruited athletes could help foster racial diversity, though he does not include this practice in his preferred simulation (explaining that it "is sometimes perceived as radical").[141]

204. Second, SFFA and Mr. Kahlenberg suggest that Harvard should increase the consideration it affords in the admissions process to students of lower socioeconomic status. Mr. Kahlenberg also suggests that, to do so, Harvard should make available to admissions officers whatever information its Financial Aid Office may possess about applicant's family income and wealth.[142]

205. Third, SFFA and Mr. Kahlenberg suggest that Harvard should increase the financial aid it offers, on the theory that doing so would attract more applicants and matriculants of lower socioeconomic status.[143]

206. Fourth, SFFA and Mr. Kahlenberg suggest that Harvard adopt geography-based preferences, such as a "percent plan" under which it would admit the top students from each high school or each ZIP code.[144]

207. Fifth, SFFA and Mr. Kahlenberg suggest that Harvard increase its efforts to recruit a

[141] Kahlenberg Report, pp. 31–34, p. 41, and p. 46.

[142] Kahlenberg Report, pp. 23–29.

[143] Kahlenberg Report, pp. 29–31.

[144] Kahlenberg Report, pp. 36–39.

diverse applicant pool.[145]

208. Sixth, SFFA and Mr. Kahlenberg suggest that Harvard could increase racial diversity by accepting more transfer applicants, particularly from community colleges.[146]

7.1.2. Additional race-neutral alternatives identified in the literature

209. I also reviewed the academic literature discussing race-neutral alternatives, and this review indicates that SFFA's list of race-neutral alternatives is generally comprehensive. One race-neutral strategy for increasing racial diversity that SFFA does not mention but that is discussed in the academic literature is reducing or eliminating consideration of standardized test scores. That strategy is predicated on the theory that standardized tests may advantage students who attend better schools and have more resources for test preparation, who are more likely to be White or Asian-American.[147] For completeness, I include this practice in my analyses below.

7.2. Academic research indicates that race-neutral alternatives diminish universities' ability to select for quality

210. Many academics have studied the efficacy of race-neutral alternatives in generating a high-quality, racially diverse student body without considering race in the admissions process. While there is general agreement that race-neutral alternatives can help increase racial diversity relative to an admissions regime that does not consider race, there is little empirical evidence that race-neutral alternatives have produced diverse student bodies comparable to those attained under race-conscious regimes at selective institutions, where researchers note that race-neutral policies may be less effective.[148] Furthermore, the literature indicates that the replacement of race-conscious admissions with race-neutral alternatives introduces an unavoidable tradeoff between the quality and racial

[145] Kahlenberg Report, pp. 39–40.

[146] Kahlenberg Report, pp. 41–42.

[147] John Brittain and Benjamin Landy, "Reducing Reliance on Testing to Promote Diversity," in *The Future of Affirmative Action*, ed. Richard Kahlenberg (Century Foundation Press, 2014), pp. 160–174 at p. 161; Anthony P. Carnevale, Stephen J. Rose, and Jeff Strohl, "Achieving Racial and Economic Diversity with Race-Blind Admissions Policy," in *The Future of Affirmative Action*, ed. Richard Kahlenberg (Century Foundation Press, 2014), pp. 187–202 at pp. 189 and 193.

[148] Halley Potter, "Transitioning to Race-Neutral Admissions: An Overview of Experiences in States Where Affirmative Action Has Been Banned," in *The Future of Affirmative Action*, ed. Richard Kahlenberg (Century Foundation Press, 2014), pp. 75–90 at pp. 88–89; Thomas J. Kane, "Racial and Ethnic Preferences in College Admissions," *Ohio St. Law Journal* 59, 1998, pp. 971–996 at pp. 972 and 992; Sean Reardon, Rachel Baker, and Daniel Klasik, "Race, income, and enrollment patterns in highly selective colleges, 1982-2004," *Center for Education Policy Analysis*, Stanford University, 2012, pp. 1–25 at p. 4.

diversity of an admitted class. In essence, the literature concludes, universities that attempt to achieve racial diversity without considering race have lesser ability to choose the highest-quality class than if they were able to consider race.[149]

7.2.1. Race-neutral alternatives do not achieve the same level of racial diversity as race-consciousness at selective universities

211. Economic research on alternative admissions policies firmly supports the effectiveness of race-conscious admissions in achieving racial diversity at selective institutions. The economic literature studying attempts to produce racial diversity *without* considering race tends to focus on the efficacy of race-neutral alternatives in generating a substantial fraction of African-American and Hispanic students, largely because those are the groups whose representation falls most significantly when universities remove consideration of race from admissions.

212. Thomas Espenshade and Chang Chung (2005), for example, conduct simulations for three elite private research universities (which they do not identify). They find that eliminating the consideration of race in admissions would notably reduce the share of African-American and Hispanic students among admitted students, and that consideration of lineage and athletic-recruit status has little effect on African-American and Hispanic representation.[150]

213. Economic research regarding bans on race-conscious admissions in Texas, Florida, California, and Washington suggests that those bans adversely affected racial diversity, especially at more selective schools.[151] A separate analysis of the California ban studied the efficacy of a battery of alternative admissions practices, including a preference for applicants of low socioeconomic status.

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[149] Jimmy Chan and Erik Eyster, "Does Banning Affirmative Action Lower College Student Quality?," *American Economic Review* 93(3), 2003, pp. 858–872 at pp. 858–856; Mark Long, "Is There a 'Workable' Race-Neutral Alternative to Affirmative Action in College Admissions?," *Journal of Policy Analysis and Management* 34(1), 2015, pp. 162–183 at p. 167; Mark Long, "The Promise and Peril for Universities Using Correlates of Race in Admissions in Response to the *Grutter* and *Fisher* Decisions," *ETS White Paper*, 2015, pp. 1–31 at p. 13; Glenn Ellison and Parag Pathak, "The Efficiency of Race-Neutral Alternatives to Race-Based Affirmative Action: Evidence from Chicago's Exam Schools," *NBER Working Paper* #22589, 2016, pp. 1–59 at p. 51; Roland Fryer, Glenn Loury, and Tolga Yuret, "An Economic Analysis of Color-Blind Affirmative Action," *The Journal of Law, Economics, & Organization* 24(2), 2007, pp. 319–355 at p. 1; Roland Fryer and Glenn Loury, "Affirmative Action and Its Mythology," *The Journal of Economic Perspectives* 19(3), 2005, pp. 147–162 at pp. 150–153.

[150] Thomas Espenshade and Chang Y. Chung, "The opportunity cost of admission preferences at elite universities," *Social Science Quarterly* 86(2), 2005, pp. 293–305 at p 298.

[151] Peter Hinrichs, "The effects of affirmative action bans on college enrollment, educational attainment, and the demographic composition of universities," *The Review of Economics and Statistics* 94(3), 2012, pp. 712–722 at p. 712.

None of the alternative practices analyzed was able to produce a student body with diversity comparable to that predating the ban on race-conscious admissions practices.[152]

7.2.2. Much of the literature focuses on universities far less selective than Harvard

214. While some universities have used race-neutral alternatives with moderate success in achieving racial diversity, those universities tend to be far less selective than Harvard, making it easier for them to attract applicants who do not reduce the quality or alter the character of the student body. Halley Potter, a colleague of Mr. Kahlenberg on whose work he relies, studied eleven flagship state universities that were barred from using race in admissions. Of those eleven schools, seven were able to achieve African-American and Hispanic enrollment comparable to that attained before the ban; four were not. Importantly, the three most selective schools in the sample—UC-Berkeley, Michigan, and UCLA, the schools most similar to Harvard—were among the four schools not able to attain pre-ban levels of representation for African American and Hispanic students.[153] As Potter explains, scholars have yet to identify race-neutral strategies that work well for selective institutions:

> Selective colleges have a smaller pool of qualified applicants to begin with, and these applicants are more likely to be considering a variety of in- and out-of-state college options. As a result, selective colleges may face greater challenges in terms of recruiting additional applicants from underrepresented demographics… [I]dentifying effective diversity strategies for selective campuses under race-neutral admissions is an important area for future research.[154]

215. Instead of focusing on the efficacy of race-neutral alternatives at selective institutions, Mr. Kahlenberg chooses to highlight the handful of large, less selective public schools that (he argues) were able to employ race-neutral alternatives to attain diverse classes comparable to those before the consideration of race was banned. Examples include Texas A&M, the University of Washington, the University of Nebraska, the University of Arizona, and the University of Georgia.[155]

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[152] Daniel Koretz, Michael Russell, Chingwei David Shin, Cathy Horn, Kelly Shasby, "Testing and Diversity in Postsecondary Education: The Case of California," *Education Policy Analysis Archives* 10(1), 2002, pp. 1–39 at pp. 27–28.

[153] The fourth university that failed to regain pre-bar levels of representation for both African-American and Hispanic students was the University of New Hampshire. (Halley Potter, "Transitioning to Race-Neutral Admissions: An Overview of Experiences in States Where Affirmative Action Has Been Banned," in *The Future of Affirmative Action*, ed. Richard Kahlenberg (Century Foundation Press, 2014), pp. 75–90 at p. 89.)

[154] Halley Potter, "Transitioning to Race-Neutral Admissions: An Overview of Experiences in States Where Affirmative Action Has Been Banned," in *The Future of Affirmative Action*, ed. Richard Kahlenberg (Century Foundation Press, 2014), pp. 75–90 at p. 89.

[155] Kahlenberg Report, p. 6.

But those schools' experience sheds little light on how race-neutral alternatives would fare at Harvard, a far smaller and far more selective institution. As I show below, any strategies used by larger and less selective universities, such as percent plans or increased transfers from community colleges, are likely to generate a pool of applicants who are less qualified than Harvard's current applicants.

7.2.3. The literature shows that an increased preference for applicants of lower socioeconomic status can achieve racial diversity only at the cost of reducing the quality of the admitted class on a range of dimensions that I understand Harvard considers important

216. Mr. Kahlenberg places heavy emphasis on the idea that universities can achieve racial diversity without considering race by according a significant admissions preference to applicants of low socioeconomic status (SES). In my view, however, the literature does not support that conclusion. (Nor, as I will discuss later, do simulations using Harvard's data.)

217. It is widely understood as a matter of economic theory that if a university is forced to target an imperfect correlate of race to achieve racial diversity, it is less able to choose the highest-quality class than if it considered race directly.[156] Giving a strong admission preference to low-SES candidates can indirectly generate racial diversity because some SES measures are correlated with race. But because SES is not a perfect proxy for race, universities must place a significant weight on SES measures to obtain substantial racial diversity—above and beyond what would be optimal for creating a high-quality class in other dimensions. Even when the link between SES and race is strong, this high degree of emphasis on SES factors can significantly alter the characteristics of the admitted class.

218. Mr. Kahlenberg cites literature selectively in attempting to diminish the well supported principle that targeting correlates of race will always be a more costly way to generate racial diversity (in terms of the costs it imposes on other attributes of the admitted class) than considering race itself.

[156] Jimmy Chan and Erik Eyster, "Does Banning Affirmative Action Lower College Student Quality?," *American Economic Review* 93(3), 2003, pp. 858–872 at pp. 858–859; Mark Long, "Is There a 'Workable' Race-Neutral Alternative to Affirmative Action in College Admissions?," *Journal of Policy Analysis and Management* 34(1), 2015, pp. 162–183 at p. 167; Mark Long, "The Promise and Peril for Universities Using Correlates of Race in Admissions in Response to the *Grutter* and *Fisher* Decisions," *ETS White Paper*, 2015, pp. 1–31 at p. 13; Glenn Ellison and Parag Pathak, "The Efficiency of Race-Neutral Alternatives to Race-Based Affirmative Action: Evidence from Chicago's Exam Schools," *NBER Working Paper* #22589, 2016, pp. 1–59 at p. 51; Roland Fryer, Glenn Loury, and Tolga Yuret, "An Economic Analysis of Color-Blind Affirmative Action," *The Journal of Law, Economics, & Organization* 24(2), 2007, pp. 319–355 at pp. 319–320; Roland Fryer and Glenn Loury, "Affirmative Action and Its Mythology," *The Journal of Economic Perspectives* 19(3), 2005, pp. 147–162 at pp. 150–153.

For example, Mr. Kahlenberg cites the work of Richard H. Sander and Aaron Danielson, who (in Mr. Kahlenberg's words) suggest that "richer measures of socioeconomic status … significantly increased the correlation between race and socioeconomic status and the racial dividend of class-based affirmative action."[157] But Mr. Kahlenberg fails to note that these same authors also assert that "[i]t is axiomatic that no race-neutral factor or system can be as *efficient* as using race itself to achieve racial diversity through an admissions program … The high academic costs of the larger SES preferences in these models would, we think, render it unpalatable to most selective schools."[158]

219. Mr. Kahlenberg also cites Matthew N. Gaertner's 2014 study of race-neutral alternatives at the University of Colorado to support the claim that preferences for applicants of low socioeconomic status can "achieve even *more* racial diversity than using racial preferences."[159] But Mr. Kahlenberg neglects Gaertner's warning that such policies are complicated to implement and may lower the academic quality of the admitted class and the likelihood of success for admitted students.[160]

220. Mr. Kahlenberg draws on the work of Anthony P. Carnevale, Stephen J. Rose, and Jeff Strohl, who simulate several race-blind admissions regimes. The authors do find that these approaches can produce racial diversity, but only "if elite colleges are willing to risk lower average test scores … and thereby lower graduation rates."[161]

221. Mr. Kahlenberg also cites work by Anthony P. Carnevale and Stephen J. Rose to support his claim that "top universities could nearly quadruple the proportion of students from the bottom

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[157] Kahlenberg Report, p. 19.

[158] Aaron Danielson and Richard H. Sander, "Thinking Hard About 'Race-Neutral' Admissions," *University of Michigan Journal of Law Reform* 47(4), 2014, pp. 967–1020, at pp. 968 and 995.

[159] Kahlenberg Report, p. 12.

[160] Matthew N. Gaertner, "Advancing College Access with Class-Based Affirmative Action," in *The Future of Affirmative Action*, ed. Richard Kahlenberg (Century Foundation Press, 2014), pp. 175–186 at pp. 183–184 ("Table 114.5 suggests that on average, class-based admits can be expected to perform worse in college than typical undergraduates…These patterns should not be terribly surprising, given that class-based admits are 'borderline' applicants—students on the cusp of admission whose academic credentials are not stellar, and whose personal qualities weigh more heavily in an admissions decision[]" and "Across outcomes, strictly overachieving class-based admits can be expected to perform quite well—better, in fact, than typical undergraduates. The forecasts for strictly disadvantaged admits, however, are not as encouraging. Their GPAs, graduation rates, and earned credit hours lag far behind the baseline.").

[161] Anthony P. Carnevale, Stephen J. Rose, and Jeff Strohl, "Achieving Racial and Economic Diversity with Race-Blind Admissions Policy," in *The Future of Affirmative Action*, ed. Richard Kahlenberg (Century Foundation Press, 2014), pp. 187–202 at p. 188.

socioeconomic half … without any change in graduation rates."[162] But he fails to note that in the simulation he references, African-American representation fell by a third, suggesting that the simulated admissions regime was ineffective at producing racial diversity even if it generated socioeconomic diversity.[163] Indeed, Carnevale and Rose concluded that "ultimately there is no better way to guarantee a certain level of racial diversity than by employing race per se" and that "[w]hile socioeconomic preferences help produce some racial diversity, a credible procedure that can reproduce the level of racial diversity that exists in society today without purposely singling out African Americans and Hispanics at some point in the selection process has yet to be found."[164]

222. Finally, Mr. Kahlenberg also cites the work of Sigal Alon, highlighting a set of Alon's simulations, which, he argues, show that "if the most selective 115 American universities instituted broad reform—including effectively eliminating lineage, athletic, and racial preferences—a socioeconomic boost 'could not only replicate the current level of racial and ethnic diversity at elite institutions but even increase it.'"[165] But Alon's simulations do not consistently show that African-American and Hispanic representation would meet or exceed the levels achieved by considering race. Furthermore, in the one simulation where the fraction of African-American and Hispanic admitted students exceeds the levels achieved by considering race, Alon notes that the "price" of this racial diversity "would be a decline in academic selectivity."[166] He also notes that those policy changes would substantially increase the cost of providing financial aid.[167]

223. Far from buttressing his claim that preferences for low-SES applicants can enable selective colleges to increase racial diversity without harming the quality of their student bodies, the literature Mr. Kahlenberg cites specifically highlights the challenges and costs of such policies for a selective school like Harvard.

7.2.4. Conclusion

224. In sum, my review of the literature indicates that while race-neutral alternatives can be used to increase racial diversity relative to a regime that does not consider race at all, (1) they typically do not produce diverse student bodies comparable to those attained using race-conscious

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[162] Kahlenberg Report, p. 14.

[163] Anthony P. Carnevale and Stephen J. Rose, "Socioeconomic Status, Race/Ethnicity, And Selective College Admissions," in *America's Untapped Resource: Low Income Students*, ed. Richard Kahlenberg (Century Foundation Press, 2004), pp 101–156 at p. 148.

[164] Anthony P. Carnevale and Stephen J. Rose, "Socioeconomic Status, Race/Ethnicity, And Selective College Admissions," in *America's Untapped Resource: Low Income Students*, ed. Richard Kahlenberg (Century Foundation Press, 2004), pp 101–156 at pp. 150 and 153.

[165] Kahlenberg Report, p. 13.

[166] Sigal Alon, *Race, Class, and Affirmative Action* (New York, NY: Russell Sage Foundation, 2015), pp. 254–256.

[167] Sigal Alon, *Race, Class, and Affirmative Action* (New York, NY: Russell Sage Foundation, 2015), p. 256

admissions at selective institutions, and (2) both as a theoretical matter and in practice, they reduce the quality of the admitted class. As I show in the remainder of this section, my analysis of Harvard's admissions data bear out the consensus in the literature: Harvard is unlikely to be able to achieve a comparably diverse student body without considering race and without decreasing the overall quality of the admitted class on a variety of dimensions.

7.3. Analysis of race-neutral alternatives using Harvard's admissions data

225. In this section, I evaluate how Harvard's class would change under race-neutral alternatives identified in the academic literature discussed above, including those alternatives suggested by the Complaint and Mr. Kahlenberg. I employ two methodological approaches in my analysis.

226. First, I simulate how the use of certain race-neutral alternatives would be expected to change the demographic and other characteristics of the admitted class. Consistent with the broader academic literature, I find that any of the race-neutral alternatives proposed by SFFA or Mr. Kahlenberg that would achieve a class with comparable ethnic and racial diversity would do so only by changing other attributes of the class in ways that I understand matter to Harvard.

227. Second, for race-neutral practices that Harvard has already employed or experimented with in the past (i.e., increased financial aid and the elimination of Early Action admissions), I examine historical data to assess whether further changes could help achieve racial diversity. I find that (a) eliminating Early Action is unlikely to foster additional racial diversity, and (b) given Harvard's current financial aid and recruiting practices, further expansions in financial aid and recruiting are unlikely to increase racial diversity.

7.3.1. Eliminating consideration of race in the admissions process

228. To simulate the effect of removing consideration of race from the admissions process, I begin by estimating my preferred year-by-year model (developed in Section 5) for applicants to the class of 2019. I then turn off the estimated coefficients on the race variables, allowing me to simulate what class would be admitted if Harvard did not consider race in the admissions process. In my simulation, the share of African-American students in the admitted class would drop from 14% to 6%. The fraction of Hispanic or Other students would fall from 14% to 9%. The fraction of admitted students who are Asian-American would rise from 24% to 27%. And the fraction of admitted students who are White would rise from 40% to 48%.[168]

[168] See Exhibit 36 for an illustration of these changes.

7.3.2. Eliminating deferred admission and consideration of whether an applicant is a lineage applicant, a child of Harvard faculty or staff, a recruited athlete, or on the Dean's or Director's interest lists

229. Mr. Kahlenberg suggests that one way a school like Harvard could attempt to increase racial diversity would be to eliminate admissions practices that allegedly benefit White applicants. The specific practices identified by Mr. Kahlenberg and addressed in his simulations include: Harvard's practice offering deferred admission to a small group of candidates, conditional on their taking a year off before matriculating; consideration of whether an applicant's parents attended Harvard or Radcliffe (i.e., whether the applicant is a "lineage" applicant); consideration of whether an applicant is the child of Harvard faculty or staff; consideration of whether an applicant is a recruited athlete; and the use of the Dean's and Director's interest lists. Mr. Kahlenberg does not remove consideration of whether an applicant is a recruited athlete in his preferred simulation (explaining that such an approach "is sometimes perceived as radical"), but I simulate the effect of that change in order to ensure that I am considering all potentially available race-neutral alternatives.

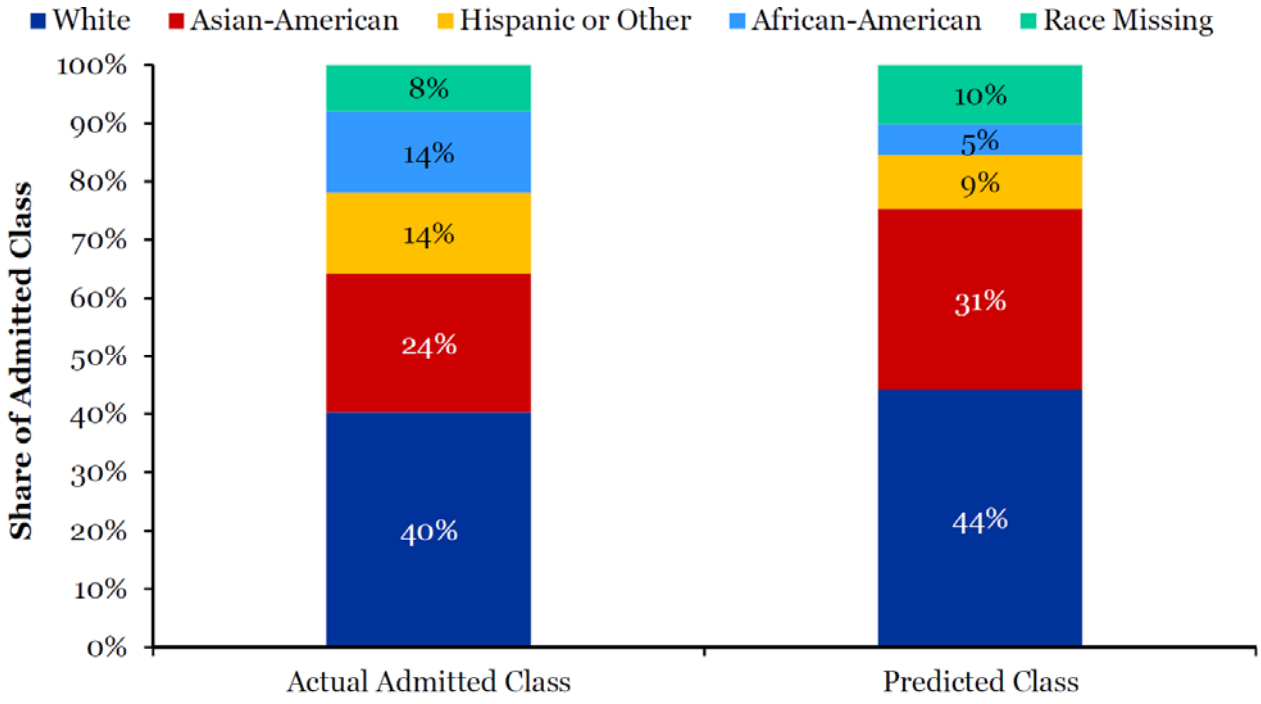
230. Using my preferred year-by-year model of admissions from Section 5, I simulate how the elimination of these practices would affect Harvard's admitted class. My method closely follows that used by Mr. Kahlenberg in his report. First, I estimate my model of admissions using data on applicants to the class of 2019.[169] Then, I simulate the effect of eliminating consideration of race, lineage status, athletic-recruit status, whether an applicant is the child of Harvard faculty or staff, and whether an applicant is on the Dean's or Director's interest lists. (I do so by replacing the estimated coefficient of the relevant variables—*e.g.*, a coefficient estimating the effect of being a lineage applicant on an applicant's likelihood of admission—with zero.) I then simulate the class that would be admitted using each applicant's predicted probability of admission in this modified model of admissions, and examine how the composition of the simulated class compares to that of the actual admitted class. Note that this method also eliminates the practice of deferred admission because it simulates filling all seats in the entering class with students who apply in a given year.

231. As Exhibit 35 shows, removing consideration of factors that allegedly benefit White applicants does little to generate racial diversity. The simulated class has more White students and many more Asian-American students, but markedly fewer African-American, Hispanic, or Other (AHO) students than Harvard now admits.

[169] Simulation results for earlier years are qualitatively similar, and can be found in the backup for the relevant exhibit.

Exhibit 35

Simulated racial composition of the admitted class, after eliminating the consideration of race, lineage, athletic-recruit status, whether an applicant's parents are Harvard faculty and staff, and the Dean's and Director's interest lists



Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty or staff, whether an applicant is on the Dean's or Director's interest list, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating.

7.3.3. Increasing the weight placed on socioeconomic factors

232. Mr. Kahlenberg also suggests that Harvard could attain a diverse class without considering race if it increased its consideration of applicants' socioeconomic status in the admissions process. To examine the likely effect of doing so, I again use my preferred admissions model to conduct a series of simulations. The simulations build on the results presented in the prior section by considering what would happen if admissions officers at Harvard did not consider race, but gave greater consideration to various indicators of lower socioeconomic status. To conduct the simulations, I proceed in several steps.

233. First, I estimate my preferred model of admissions. Then, I remove consideration of race, lineage status, recruited-athlete status, whether an applicant is the child of Harvard faculty or staff,

and whether an applicant is on the Dean's or Director's interest list.[170] Next, I simulate an increased preference for students who possess various measurable indicators of lower socioeconomic status. I do this by artificially increasing the probability of admission for applicants who meet one or more of the following criteria: (1) the admissions officer reading the applicant's file considered the applicant to be "disadvantaged," (2) neither of the applicant's parents attended college (i.e., the applicant is considered a first-generation college student), (3) the applicant requested a waiver of the application fee, or (4) the estimated median family income of students in the applicant's neighborhood is at or below $65,000 (Harvard's threshold for zero parental contribution).[171]

234. In the simulations, I introduce a low-SES boost that is proportional to the number of the criteria that an applicant meets. An applicant who meets all four criteria, for example, gets the full low-SES boost, while an applicant who meets only two criteria gets a boost equal to one-half of the full boost. I start by setting the full boost at two additional points to an applicant's admissions index (i.e., the input into the logit function that determines her probability of admission). This is about half the size of the boost simulated by Mr. Kahlenberg.[172] It is about one-quarter the size of the increase in the admissions index associated with having exceptional profile rating combinations (those with admission rates between 80% and 96%), and it is nearly one-third the size of the advantage associated with having very strong profile ratings combinations (those with admission rates between 54% and 67%).[173] An increase in an applicant's admissions index translates into an increase in her predicted probability of admission, but the size of the increase to her predicted probability of admission depends on her initial predicted probability of admission. For example, adding a low-SES boost of 2 points to the admissions index for a candidate with a 1% predicted probability of admission raises her predicted probability of admission to 7%. Adding a boost of 2 points to the linear prediction for a candidate with a 50% predicted probability of admission, however, would increase her predicted probability of admission to 88%.[174]

235. As noted above, I start by assuming a low-SES boost of 2 for an applicant who possesses all four of the indicators of low-SES status. If an applicant meets fewer than four of the criteria listed

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[170] Following Mr. Kahlenberg's approach, I recode athletes with an athletic rating of 1 to have an athletic rating of 2, assigning them to the appropriate ratings combination in the regression sample.

[171] I exclude from this simulation an indicator of whether the applicant applied for financial aid, because three-quarters of all applicants apply for aid, rendering it a poor proxy for socioeconomic disadvantage. The estimated median family income figures come from data acquired from the College Board and made available to SFFA and its experts. In these data, an applicant's neighborhood is determined based on the applicant's address. A neighborhood is defined by the College Board and consists of one or more contiguous census tracts.

[172] Mr. Kahlenberg simulates a preference that is half the size of the athletic recruit coefficient in Prof. Arcidiacono's model.

[173] These two sets of rating combinations have the highest admission rates across all rating combinations in my regression sample. See workpaper.

[174] See workpaper.

above, her baseline low-SES boost is lower. If she meets three of the criteria above, she receives a boost of 1.5; if she meets two of the criteria above, she receives a boost of 1; if she meets one of the criteria above, she receives a boost of 0.5.

236. To evaluate the impact of increasing the magnitude of the boost, I then scale up the size of each applicant's low-SES boost by a factor of 2 (denoted by 2x), 3 (denoted by 3x), and so on. For example, in later simulations where I refer to a 2x low-SES boost, I mean that an applicant in that simulation who satisfies all four low-SES criteria receives a boost of 4 points (doubled from the baseline of 2 points); an applicant who satisfies three criteria receives a boost of 3 points (doubled from the baseline of 1.5 points); and so on.

237. My method differs somewhat from Mr. Kahlenberg's method for simulating increased weight on socioeconomic factors. In his race-neutral alternative simulations—which examine the effect of multiple race-neutral practices, not just an increased preference for low-SES applicants—Mr. Kahlenberg simulates eliminating consideration of whether an applicant has been identified by admissions officers as disadvantaged, whether the applicant is a first-generation college student, whether the applicant applied for financial aid, and whether the applicant requested a fee waiver, but then simulates an increased preference only for students who are identified as disadvantaged. My approach is more inclusive and flexible, simulating an increased boost for a broader set of students of lower SES, with the size of the boost for each applicant varying with the number of indicators of low socioeconomic status that she exhibits.

238. Exhibit 36 illustrates how the racial composition of the admitted class would be expected to change if Harvard placed varying degrees of additional weight on the low-SES attributes noted above *and* eliminated the practices (discussed above) that are alleged to benefit White applicants. The first two columns in Exhibit 36 report the racial composition of the actual class and the simulated class in a world where Harvard eliminates consideration of race *without* undertaking additional race-neutral approaches to increase racial diversity. The third bar shows what would be expected to happen if, in addition to eliminating consideration of race and factors that allegedly benefit White applicants, Harvard gave each low-SES applicant an additional boost of the size discussed above in paragraph 235. The next bar shows what would happen if Harvard doubled the maximum low-SES boost, and so on.[175] Exhibit 37 summarizes the simulated change in the racial composition of the admitted class under this alternative admissions regime as compared to the actual admitted class of 2019.

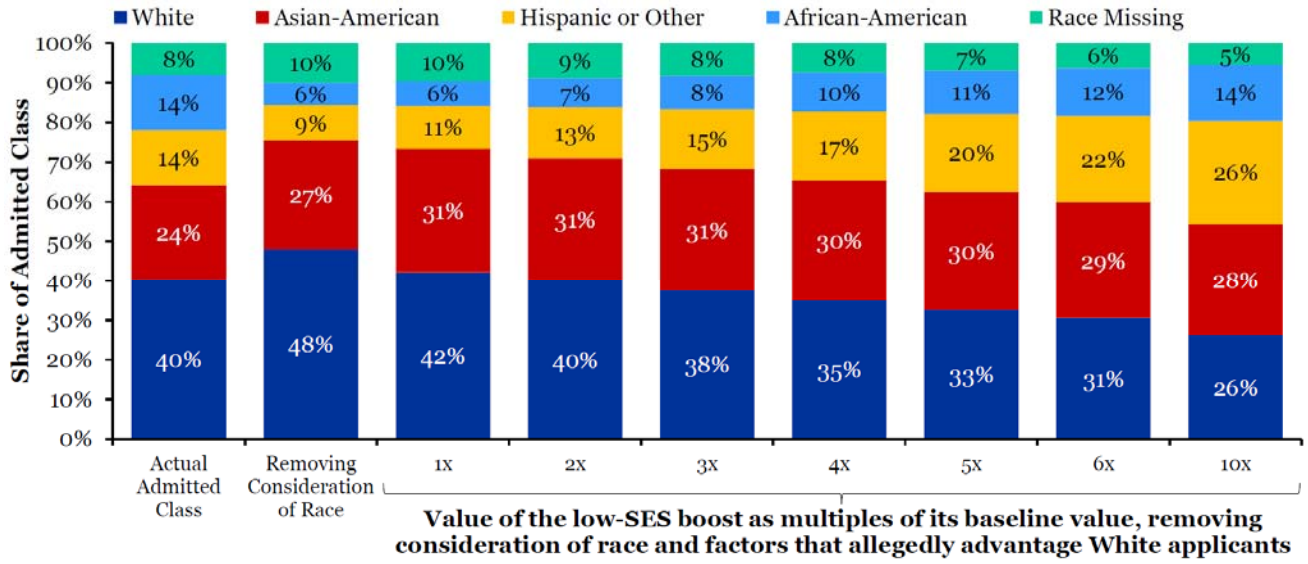
239. As noted above, if Harvard were to eliminate consideration of race, the share of African-

[175] The full range 1-10x is located in the backup to the exhibit, as are results for the classes of 2014 – 2018, which are qualitatively similar.

American students in the admitted class would be expected to drop from 14% to 6%. The fraction of Hispanic students would also fall, while the fraction of Asian-American and White students would rise. If Harvard then applied a low-SES boost (as described above) and eliminated the practices alleged to benefit White applicants, the share of African-American students in the admitted class would be expected to remain constant at 6%—still radically below the current level. The fraction of Hispanic students would rise, from 9% to 11%, remaining about 20% lower than in the actual class. The fraction of White admitted students would fall back to a level comparable to the current class, while the fraction of Asian-American students in the admitted class would grow from 27% to 31%. Harvard would need to increase the low-SES boost to more than six times the baseline (i.e., to a maximum factor of 12) in order for the expected proportion of African-American students among admitted students to approximate the current level. At that point, hundreds of low-SES applicants would be receiving an incremental boost larger than that given to candidates with the most exceptional academic, extracurricular, personal, and athletic ratings.[176]

Exhibit 36

Increasing the weight placed on socioeconomic characteristics could help generate racial diversity



Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates preferences for race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample which contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000.

[176] See workpaper.

Exhibit 37

Estimated change in racial composition after removing consideration of race, increasing weight on socioeconomic characteristics, and eliminating the practices alleged to benefit White applicants

		Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants, Change from Actual Class						
Race	Actual Admitted Class	1x Low-SES Boost	2x Low-SES Boost	3x Low-SES Boost	4x Low-SES Boost	5x Low-SES Boost	6x Low-SES Boost	10x Low-SES Boost
1. **White**	676	+34	-4	-44	-87	-127	-162	-236
2. **Asian-American**	402	+120	+118	+113	+106	+98	+90	+71
3. **Hispanic or Other**	233	-51	-18	+19	+60	+99	+133	+204
4. **African-American**	234	-130	-112	-92	-71	-51	-34	+4
5. **Race Missing**	134	+27	+16	+4	-7	-18	-26	-43

		Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants, % Change from Actual Class						
Race	Actual Admitted Class	1x Low-SES Boost	2x Low-SES Boost	3x Low-SES Boost	4x Low-SES Boost	5x Low-SES Boost	6x Low-SES Boost	10x Low-SES Boost
1. **White**	40%	+5%	-1%	-7%	-13%	-19%	-24%	-35%
2. **Asian-American**	24%	+30%	+29%	+28%	+26%	+24%	+22%	+18%
3. **Hispanic or Other**	14%	-22%	-8%	+8%	+26%	+42%	+57%	+88%
4. **African-American**	14%	-55%	-48%	-39%	-30%	-22%	-15%	+2%
5. **Race Missing**	8%	+20%	+12%	+3%	-6%	-13%	-20%	-32%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000.

240. Increasing the size of the low-SES boost in this manner would also be expected to lead to changes in the admitted class in other respects, many of which Harvard might well consider deleterious. For example, if Harvard were to increase the size of the low-SES boost by four or five times—enough for the *combined share* of AHO students in the expected class to resemble that of the current class, but still not enough to restore a comparable share of African-American students[177]—and eliminate the practices alleged to benefit White applicants, numerous measures of excellence in

[177] If Harvard increased the size of the low-SES preference four times relative to the baseline, that would yield a preference for students identified as "disadvantaged" that is roughly equivalent to the preference Mr. Kahlenberg gives them in his simulations. At five times the baseline preference, students identified as "disadvantaged" receive about one and a half times the preference in my model as in Mr. Kahlenberg's simulations. In addition, under my more flexible simulation, students who are first-generation or who receive fee waivers also receive a boost about the same size on average as the one accruing to applicants identified as "disadvantaged" (see workpaper).

Harvard's class would drop substantially. This can be seen in Exhibit 38, which summarizes changes across a variety of characteristics of the admitted class. For example, the fraction of admitted students receiving an academic rating of 1 or 2 would be expected to drop by an amount between 13% and 22%. The fraction of students receiving top extracurricular and personal ratings would also fall, and the fraction with top athletic ratings would be cut by a third. In addition, as the magnitude of the low-SES boost increases to 3x the baseline boost and beyond, the fraction of admitted students who are Asian-American begins to fall, rather than rise.

241. The admitted class would also be expected to look markedly different in other dimensions. The fraction of students intending to concentrate in the humanities and social sciences would be expected to fall, while the fraction intending to concentrate in biological sciences would be expected to rise. The fraction of admitted students who are children of Harvard and Radcliffe alumni would fall, as would the number of admitted students who are children of Harvard faculty and staff. The number of athletic recruits would drop by half.

Exhibit 38

Increasing the weight placed on socioeconomic characteristics would be expected to markedly alter the characteristics of Harvard's admitted class

		Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants					
		3x Low-SES Boost		4x Low-SES Boost		5x Low-SES Boost	
Outcome Measures	Actual Admitted Class [A]	Predicted Value [B]	% Change ([B]-[A])/[A]	Predicted Value [C]	% Change ([C]-[A])/[A]	Predicted Value [D]	% Change ([D]-[A])/[A]
Race							
1. White	676	632	-7%	589	-13%	549	-19%
2. Asian-American	402	515	+28%	508	+26%	500	+24%
3. Hispanic or Other	233	252	+8%	293	+26%	332	+42%
4. African-American	234	142	-39%	163	-30%	183	-22%
5. Race Missing	134	138	+3%	127	-6%	116	-13%
Academic							
6. Average Composite SAT Score	2244	2213	-1%	2189	-2%	2164	-4%
7. Average Composite ACT Score	33.1	33.0	-0.5%	32.7	-1%	32.4	-2%
8. Average Converted GPA	77.0	77.2	+0.3%	77.1	+0.1%	76.9	-0.1%
9. Average Academic Index	228	227	-0.4%	225	-1%	224	-2%
Fraction with Profile Rating of 1 or 2							
10. Academic	76%	72%	-5%	66%	-13%	59%	-22%
11. Extracurricular	62%	61%	-2%	57%	-9%	52%	-17%
12. Personal	71%	68%	-5%	64%	-11%	59%	-17%
13. Athletic	27%	19%	-30%	18%	-33%	17%	-38%
Applicant Characteristics							
14. Number of Lineage Students	259	104	-60%	86	-67%	68	-74%
15. Number of Double Lineage Students	72	24	-67%	19	-73%	15	-79%
16. Number of Recruited Athletes	180	89	-51%	88	-51%	88	-51%
17. Number of Children of Harvard Faculty and Staff	44	20	-54%	17	-61%	13	-69%
18. Number of Students on Dean's and Director's Interest Lists	**Redacted**						
19. Number of Female Students	839	848	+1%	851	+1%	855	+2%

Concentration							
20. Social Sciences	25%	24%	-4%	24%	-5%	23%	-7%
21. Humanities	15%	14%	-7%	13%	-9%	13%	-12%
22. Biological Sciences	21%	23%	+8%	23%	+11%	24%	+15%
23. Physical Science	7%	8%	+8%	8%	+6%	8%	+3%
24. Engineering	13%	13%	+4%	13%	+5%	14%	+8%
25. Computer Science	6%	6%	-4%	6%	-7%	6%	-9%
26. Mathematics	6%	7%	+5%	7%	+3%	6%	+2%
27. Unspecified	7%	6%	-12%	6%	-9%	6%	-6%
Geography							
28. Number Rural	59	80	+35%	87	+48%	94	+59%
29. Number in Northeast	694	627	-10%	604	-13%	582	-16%
30. Number in Midwest	207	221	+7%	217	+5%	214	+3%
31. Number in South	379	395	+4%	407	+7%	419	+11%
32. Number in West	399	437	+10%	451	+13%	464	+16%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000.

242. Additionally, raising the low-SES boost four or five times relative to the baseline would likely increase the financial need of the accepted class, as evidenced by Exhibit 39.[178] Approximately 27–32% more admitted students (or about 294–356 additional students) would be expected to apply for financial aid under this alternative regime. As of 2017, Harvard's average financial aid grant was about $50,000 per student per year. Given this estimate, this alternative regime could necessitate an increase in Harvard's financial spending by roughly $59–71 million per year (assuming all four classes at Harvard at a given time receive equivalent aid), relative to the current annual aid budget of about $170 million.[179]

[178] The increase would be particularly notable among AHO applicants, the majority of whom would now be flagged as disadvantaged under the simulation. See workpaper.

[179] Harvard University, "Harvard at a Glance," available at https://www.harvard.edu/about-harvard/harvard-glance, accessed December 14, 2017 ("More than 55 percent of Harvard College students receive scholarship aid, and the average grant this year is $50,000. Since 2007, Harvard's investment in financial aid has climbed by more than 75 percent, from $96.6 million to $170 million per year."). See workpaper.

Exhibit 39

Increasing the weight placed on socioeconomic characteristics would likely increase the financial need of Harvard's admitted class

		Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants					
		3x Low-SES Boost		4x Low-SES Boost		5x Low-SES Boost	
Socioeconomic Status	Actual Admitted Class [A]	Predicted Value [B]	% Change ([B]-[A])/[A]	Predicted Value [C]	% Change ([C]-[A])/[A]	Predicted Value [D]	% Change ([D]-[A])/[A]
1. Number First Generation College	120	342	+185%	428	+257%	508	+323%
2. Number Disadvantaged	297	714	+140%	875	+195%	1024	+245%
3. Number with Fee Waiver	309	718	+132%	880	+185%	1031	+234%
4. Number with Financial Aid	1102	1328	+21%	1396	+27%	1458	+32%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Notes: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000.

243. Taken together, this evidence suggests that Harvard could achieve a student body comparably diverse in race and ethnicity by placing greater emphasis on socioeconomic factors in the admissions process—but only with significant changes to a variety of characteristics of the admitted class, including lower profile ratings on all four dimensions (academic, extracurricular, athletic, and personal). These results are consistent with the academic literature, which indicates that using socioeconomic preferences in an effort to increase racial diversity necessarily diminishes the ability to select for applicant quality in other dimensions, relative to considering race.

7.3.4. Eliminating additional admissions policies that allegedly advantage White applicants

244. Mr. Kahlenberg also suggests that Harvard could attain racial diversity without considering race by eliminating any consideration of whether an applicant's family has donated or has the capacity to donate to Harvard.[180] Other commentators have suggested that eliminating consideration of standardized test scores could increase racial diversity. In this section, I consider whether eliminating any of these practices would create racial diversity if Harvard did not consider race. I also consider whether using these policies in combination with all of the policies considered above would generate a class comparable in diversity to Harvard's current admitted class.

[180] Kahlenberg Report, pp. 33–36.

7.3.4.1. Eliminate any consideration of whether an applicant's family could donate or has donated to Harvard

245. Mr. Kahlenberg alleges that Harvard's admissions process considers as a positive factor the propensity of an applicant's family to donate to the university, and asserts that eliminating this alleged practice could increase racial diversity.[181] I do not have data on any donations made to Harvard by the family members of applicants, so I cannot test this hypothesis directly. **Redacted Redacted**

.[182] And, as I have shown above, removing consideration of those two lists does not help improve racial diversity.

7.3.4.2. Reducing or eliminating consideration of standardized test scores

246. Some commentators have proposed that universities could increase racial diversity by reducing or eliminating reliance on standardized tests like the SAT and ACT. Such arguments rely on the theory that SAT and ACT scores are correlated with socioeconomic status, because scores can be improved by parental and school investments (e.g., SAT preparation courses), and therefore that consideration of standardized test scores could conceivably have the effect of biasing admission decisions against AHO applicants (who are more likely to be disadvantaged).[183]

247. Building on the simulation I conduct in 7.3.3, I simulate what would happen if Harvard eliminated any consideration given to the SAT (SAT I), SAT Subject Tests (SAT II), ACT, and the Academic Index (which includes standardized test scores as a component). I find that if Harvard eliminated its consideration of race and factors that Mr. Kahlenberg alleges advantage White applicants, while also giving low-SES applicants the low-SES boost discussed above, further eliminating consideration of standardized test scores would not generate a student body comparable in diversity to Harvard's current class, and would also decrease the quality of the admitted class in several respects.

248. As shown by Exhibit 40 and Exhibit 41, these practices—even taken together—are unable to produce a comparably diverse class without placing very heavy weight on low-SES status. Generating a class with AHO representation comparable to that of the current class would require

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[181] Kahlenberg Report, pp. 31, 33–34.

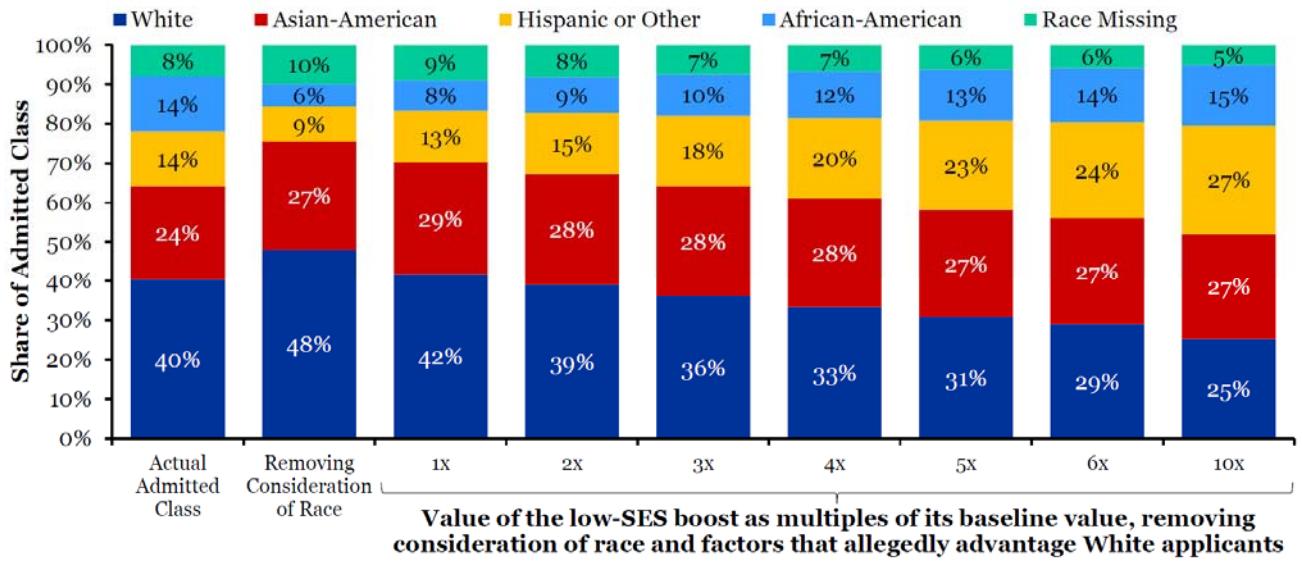
[182] Kahlenberg Report, pp. 33–36.

[183] Saul Geiser and Maria Veronica Santelices, "Validity of High-School Grades in Predicting Student Success beyond the Freshman Year: High-School Record vs. Standardized Tests as Indicators of Four-Year College Outcomes," Research & Occasional Paper Series CSHE 6.07, 2007, pp. 1–35, at pp. 1–2 and 24; Thomas Espenshade and Chang Chung, "Diversity Outcomes of Test-Optional Policies," *SAT Wars, The Case for Test-Optional Admissions*, ed. Joseph A. Soares (Teachers College Press, 2011), pp. 177–200, at p. 190.

raising the low-SES boost to three times the baseline value. And that would come at a cost (Exhibit 42). A class with a share of AHO students comparable to that of the current class (shown in the 3x bar) would exhibit a 17% decline in the fraction of applicants with top academic ratings, as well as drops in the fraction of students with top extracurricular and personal ratings. The fraction of Asian-American students would also start to decline slightly as more weight is placed on low-SES status. Athletic ratings would become worse, and the number of athletic recruits would drop, as would the representation of lineage applicants. In addition, the financial need of the class would increase a great deal, generating substantial costs to Harvard (Exhibit 43). Generating an admitted class with number of African-American students comparable to that of the current admitted class (the 6x bar below) would come with even greater costs in these dimensions, including double-digit drops in the fraction of applicants with top ratings across all four profile ratings.

Exhibit 40

Eliminating consideration of standardized test scores in conjunction with other race-neutral policies: Racial composition



Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, standardized test scores, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000.

Exhibit 41

Eliminating consideration of standardized test scores in conjunction with other race-neutral policies: Changes in racial composition

Race	Actual Admitted Class	Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants, Change from Actual Class: 1x Low-SES Boost	2x Low-SES Boost	3x Low-SES Boost	4x Low-SES Boost	5x Low-SES Boost	6x Low-SES Boost	10x Low-SES Boost
1. **White**	676	+25	-22	-70	-117	-158	-190	-252
2. **Asian-American**	402	+77	+74	+69	+63	+58	+53	+47
3. **Hispanic or Other**	233	-13	+26	+68	+110	+147	+176	+229
4. **African-American**	234	-104	-82	-58	-36	-17	-2	+23
5. **Race Missing**	134	+16	+4	-9	-20	-29	-36	-47

Race	Actual Admitted Class	Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants, % Change from Actual Class: 1x Low-SES Boost	2x Low-SES Boost	3x Low-SES Boost	4x Low-SES Boost	5x Low-SES Boost	6x Low-SES Boost	10x Low-SES Boost
1. **White**	40%	+4%	-3%	-10%	-17%	-23%	-28%	-37%
2. **Asian-American**	24%	+19%	+18%	+17%	+16%	+14%	+13%	+12%
3. **Hispanic or Other**	14%	-6%	+11%	+29%	+47%	+63%	+76%	+98%
4. **African-American**	14%	-45%	-35%	-25%	-15%	-7%	-1%	+10%
5. **Race Missing**	8%	+12%	+3%	-6%	-15%	-22%	-27%	-35%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, standardized test scores, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000.

Exhibit 42

Eliminating deferred admission and consideration of standardized test scores in conjunction with other race-neutral policies: Changes in class quality

		Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants					
		2x Low-SES Boost		3x Low-SES Boost		4x Low-SES Boost	
Outcome Measures	Actual Admitted Class [A]	Predicted Value [B]	% Change ([B]-[A])/[A]	Predicted Value [C]	% Change ([C]-[A])/[A]	Predicted Value [D]	% Change ([D]-[A])/[A]
Race							
1. White	676	654	-3%	606	-10%	559	-17%
2. Asian-American	402	476	+18%	471	+17%	465	+16%
3. Hispanic or Other	233	259	+11%	301	+29%	343	+47%
4. African-American	234	152	-35%	176	-25%	198	-15%
5. Race Missing	134	138	+3%	125	-6%	114	-15%
Academic							
6. Average Composite SAT Score	2244	2198	-2%	2172	-3%	2145	-4%
7. Average Composite ACT Score	33.1	32.7	-1%	32.4	-2%	32.1	-3%
8. Average Converted GPA	77.0	76.8	-0.2%	76.6	-0.4%	76.5	-1%
9. Average Academic Index	228	225	-1%	224	-2%	222	-3%
Fraction with Profile Rating of 1 or 2							
10. Academic	76%	69%	-9%	63%	-17%	56%	-26%
11. Extracurricular	62%	62%	+0.3%	58%	-7%	53%	-15%
12. Personal	71%	70%	-1%	66%	-7%	61%	-14%
13. Athletic	27%	20%	-23%	19%	-27%	18%	-31%
Applicant Characteristics							
14. Number of Lineage Students	259	112	-57%	93	-64%	73	-72%
15. Number of Double Lineage Students	72	25	-65%	20	-72%	16	-78%
16. Number of Recruited Athletes	180	93	-48%	92	-49%	91	-49%
17. Number of Children of Harvard Faculty and Staff	44	22	-51%	18	-59%	14	-67%
18. Number of Students on Dean's and Director's Interest Lists	Redacted						
19. Number of Female Students	839	866	+3%	869	+4%	872	+4%

Concentration							
20. Social Sciences	25%	24%	-2%	24%	-3%	23%	-6%
21. Humanities	15%	14%	-3%	14%	-6%	13%	-10%
22. Biological Sciences	21%	23%	+7%	24%	+11%	25%	+16%
23. Physical Science	7%	8%	+2%	7%	+0.03%	7%	-2%
24. Engineering	13%	13%	+1%	13%	+2%	13%	+5%
25. Computer Science	6%	6%	-8%	6%	-11%	5%	-12%
26. Mathematics	6%	7%	+2%	6%	+1%	6%	-0.3%
27. Unspecified	7%	6%	-8%	6%	-5%	7%	-3%
Geography							
28. Number Rural	59	77	+30%	85	+43%	92	+55%
29. Number in Northeast	694	646	-7%	622	-10%	597	-14%
30. Number in Midwest	207	224	+8%	219	+6%	216	+4%
31. Number in South	379	379	-0.1%	390	+3%	403	+6%
32. Number in West	399	431	+8%	448	+12%	463	+16%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, standardized test scores, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000.

Exhibit 43

Eliminating deferred admission and consideration of standardized test scores in conjunction with other race-neutral policies: Changes in financial need

		Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants					
		2x Low-SES Boost		**3x Low-SES Boost**		**4x Low-SES Boost**	
Socioeconomic Status	**Actual Admitted Class** [A]	**Predicted Value** [B]	**% Change** ([B]-[A])/[A]	**Predicted Value** [C]	**% Change** ([C]-[A])/[A]	**Predicted Value** [D]	**% Change** ([D]-[A])/[A]
1. Number First Generation College	120	303	+152%	395	+229%	483	+303%
2. Number Disadvantaged	297	649	+118%	820	+176%	981	+230%
3. Number with Fee Waiver	309	662	+114%	835	+170%	1001	+224%
4. Number with Financial Aid	1102	1306	+19%	1378	+25%	1445	+31%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, standardized test scores, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000.

7.3.5. Expanding policies that may increase racial diversity

249. In this section I consider how the racial composition and quality of the admitted class would likely change if Harvard were to further expand transfer admissions, outreach, and recruiting efforts. First, I discuss these practices individually. Then, I employ a simulation to demonstrate that even if Harvard were able to double the number of applicants flagged as disadvantaged through outreach and recruiting efforts—which is unlikely—these practices, in addition to all the other race-neutral alternatives discussed above, would not produce a class comparable in diversity to the one Harvard currently admits.

7.3.5.1. Increasing transfer admissions

250. Mr. Kahlenberg suggests that recruiting and accepting more transfer applicants—particularly from community colleges—would increase racial diversity because transfer students are more racially diverse than applicants to the freshman class. I do not have data on the pool of potential transfer applicants from community colleges, so I cannot simulate the impact of a large preference for such students on class composition and quality. Data on current transfer applicants, however, suggest that such a policy is not likely to be effective.

251. First, it is important to note that Harvard rarely admits transfer students. For example, only 17 transfer applicants were accepted during the admissions cycle for the freshman class of 2019.[184] For Harvard to admit a significantly greater number of transfer students, as Mr. Kahlenberg proposes, would be a dramatic change. Given how few students drop out of Harvard, a sizable increase in the number of transfer students would require Harvard to reserve spots for transfer students by admitting a substantially smaller freshman class.[185]

252. Second, the current pool of transfer applicants is not more diverse than the regular applicant pool. If anything, transfer applicants are less likely than regular applicants to be AHO. Furthermore, the current pool of transfer applicants has lower academic credentials and ratings (on average) than the freshman applicant pool.[186] Taken together, these facts suggest that increasing the number of transfer students is not likely to increase diversity while preserving class quality.

[184] See workpaper.

[185] Four- and six-year graduation rates by race, HARV00003906; Harvard College, "What is Harvard's graduation rate?," available at https://college.harvard.edu/what-harvards-graduation-rate, accessed December 5, 2017 ("The College's graduation rate is normally 98 percent").

[186] See workpaper.

7.3.5.2. Increasing outreach and recruiting

253. SFFA and Mr. Kahlenberg identify increased outreach and recruiting as a tool to increase racial diversity. SFFA asserts, in particular, that Harvard could increase racial diversity by (1) sponsoring campus visits and outreach programs targeting underrepresented high schools, (2) sending brochures to minority applicants, and (3) recruiting more heavily in disadvantaged geographic regions.[187] Mr. Kahlenberg argues that Harvard does a "poor job" recruiting first-generation students and students from economically disadvantaged geographic areas.[188]

254. Mr. Kahlenberg cites research by Caroline Hoxby and Christopher Avery indicating that recruiting and informational outreach are crucial to attracting top talent from underrepresented communities.[189] Based on the materials I have reviewed, I understand that Harvard embraces that idea. None of the findings cited by Mr. Kahlenberg suggests that Harvard could markedly increase the racial diversity of its admitted class by engaging in further outreach, because Harvard already well understands the need to engage in outreach, and already engages in extensive efforts on this front.[190]

255. For example, Harvard's Undergraduate Minority Recruitment Program (UMRP) endeavors to spread awareness about Harvard's diverse campus community, and the Harvard application process, among middle- and high school students. Among other initiatives, the UMRP "sends targeted mailings to many potential applicants of different racial and ethnic backgrounds, coordinates robust online and social media communications, sends staff to schools and events around the world, and enlists current students to talk with potential students (both at Harvard and during hometown recruiting trips, in which enrolled Harvard students travel to their hometowns on behalf of

[187] Complaint, pp. 78–81

[188] Kahlenberg Report, pp. 39–40.

[189] Kahlenberg Report, pp. 14–15.

[190] Email from Jeff A. Neal to William Fitzsimmons, "Draft Gazette Article with Tuition/Smith," March 24, 2014, HARV00027590 – 97 at HARV00027594 ("Recruitment begins each year with direct outreach to promising juniors. … 'Recruitment has provided the foundation for Harvard's pursuit of excellence for many decades'…'Members of the Undergraduate Minority Recruitment Program (UMRP) and the Harvard Financial: Aid Initiative (HFAI) played a key role in attracting this year's students'…Members of both organizations telephoned and sent email messages and letters to prospective applicants. They also conducted recruitment trips around the country and met with middle school and high school student groups who visited Harvard.").

Harvard to conduct outreach to potential students in the area)."[191]

256. The Harvard First Generation Program (HFGP) engages in outreach to students who would be the first members of their families to attend a four-year college. "The First Generation program includes a dedicated recruitment program accessible through Harvard's website, promotional materials, and the ability to correspond directly with current First Generation students attending Harvard."[192]

257. Harvard also engages in a variety of other outreach efforts. For example, the Harvard College Connection (HCC) uses social media to reach out to promising students and encourage them to apply to Harvard.[193] Harvard's Project Teach connects Harvard with seventh-grade students in the Cambridge public schools, providing classroom materials for teachers, programs for students, and tools for families to facilitate conversations about college preparation. The Crimson Summer Academy brings together local public school students for summer classes, field trips, and college preparatory activities. Similarly, the Cambridge-Harvard Summer Academy (CHSA) allows high school students to participate in summer enrichment from teachers affiliated with the Harvard Graduate School of Education. Harvard maintains a close partnership with local public school Cambridge Rindge and Latin School, engaging its students in tutoring, free summer school courses, and scholarships to the Harvard Extension School.[194]

258. Harvard also purchases "search lists" from testing agencies to aid in identifying talented minority and rural applicants.[195] In 2013, the search lists included more than 30,000 SAT, ACT, and AP test takers who were AHO, as well as about 44,000 AHO applicants with PSAT scores greater

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[191] Harvard's Objections and Responses to Plaintiff's Second Set of Interrogatories, July 20, 2017 ("Second Interrogatory Response"), p. 15.

[192] Second Interrogatory Response, pp. 14–15.

[193] Harvard College, "Harvard College Connection," available at https://college.harvard.edu/admissions/hear-our-students/harvard-college-connection, accessed December 12, 2017.

[194] Harvard University, "Harvard in the Community," 2016, available at https://hwpi.harvard.edu/files/comm/files/2016_cambridge_impact_mailing.pdf, accessed November 27, 2017; Cambridge Rindge and Latin School, "Support & Enrichment Programs," available at http://crls.cpsd.us/academics/support___enrichment_programs, accessed November 27, 2017.

[195] Email from Jeff A. Neal to William Fitzsimmons, "Draft Gazette Article with Tuition/Smith," March 24, 2014, HARV00027590 – 97 at HARV00027594 ("More than 63 percent of all admitted students and 81 percent of admitted minority students (including 90 percent of Latinos and 83 percent of African Americans) appeared on the original College Board and ACT search lists that helped launch Harvard's outreach program for the Class of 2018."); McGrath Deposition 2015 at p. 11; Yong Deposition at pp. 264–267; Tables, "Class of 2017 – EA Applicants," HARV00007766 – 7771; Table, "Searches 2013 – Class of 2018," HARV0023564.

than 1100. Harvard used the PSAT, SAT, ACT, and AP search lists to send more than 100,000 letters to potential applicants to the class of 2018. Harvard casts a wide net when trying to attract applicants from diverse backgrounds.

259. Furthermore, admissions officers travel the country—and the world—seeking out top talent.[196] "Harvard sends representatives, including admissions officers and alumni, to conduct numerous recruitment events throughout the United States, including events targeting students at secondary schools that do not frequently send students to Harvard."[197]

260. Mr. Kahlenberg attempts to simulate the potential effects on racial diversity of improved recruiting efforts. In several of his simulations, he assumes that Harvard could double the number of applicants who are identified as disadvantaged by Harvard's admissions officers. He does this by duplicating the records for all disadvantaged applicants, implicitly assuming that the quality of newly recruited disadvantaged students would be the same as that of students who already apply. I find it unlikely (given the current depth and breadth of Harvard's recruiting efforts) that increased recruiting would produce such an influx of disadvantaged applicants,[198] and that those applicants would be as qualified as current applicants.[199] Mr. Kahlenberg has provided no evidence that this would be possible or likely.

261. I nevertheless consider how such a response might affect Harvard's admitted class. Following Mr. Kahlenberg's lead, I repeat the simulation outlined in Section 7.3.3, this time artificially doubling the number of disadvantaged students in the applicant pool by duplicating all

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[196] Email from Jeff A. Neal to William Fitzsimmons, "Draft Gazette Article with Tuition/Smith," March 24, 2014, HARV00027590 – 7 at HARV00027594 ("Last year, Harvard admissions officers visited all 50 states, Puerto Rico, Jamaica, and Mexico, where we saw nearly 50,000 high school students and parents and met with more than 3,000 high school guidance counselors" and "Staff members will visit 125 cities this spring and fall in tandem with Duke University, Georgetown University, the University of Pennsylvania, and Stanford University, targeting high school juniors who may eventually join the Class of 2019.").

[197] Second Interrogatory Response, p. 14.

[198] Researchers suggest that there is a pool of talented low-income students who do not apply to selective institutions, but the same researchers also note the difficulty of reaching these students, let alone doubling the number of such applicants. These students—dubbed "the missing one-offs" by economists Caroline Hoxby and Christopher Avery—are often "isolated from other high achievers, both in terms of geography and in terms of the high schools they attend," making recruitment efforts challenging. Notably, the authors suggest that two possible interventions consist of tapping into alumni networks to reach students at a wide array of high schools, and targeted informational interventions through mail, online, and social media—types of policies Harvard already employs. Caroline Hoxby and Christopher Avery, "The Missing "One-Offs": The Hidden Supply of High-Achieving, Low-Income Students," Brookings Papers on Economic Activity, vol. 2013(1), pp. 1–65 at p. 2 and 45.

[199] If one assumes that a disadvantaged student is more likely to apply to Harvard the more exceptional her credentials, then additional disadvantaged applicants recruited into the pool may be less qualified, on average, than current applicants. In that sense, assuming no loss to quality as the applicant pool expands is extremely conservative. Harvard's current disadvantaged applicants are a highly selected group; for example, their SAT scores are well above average for low-income students in general (see workpaper).

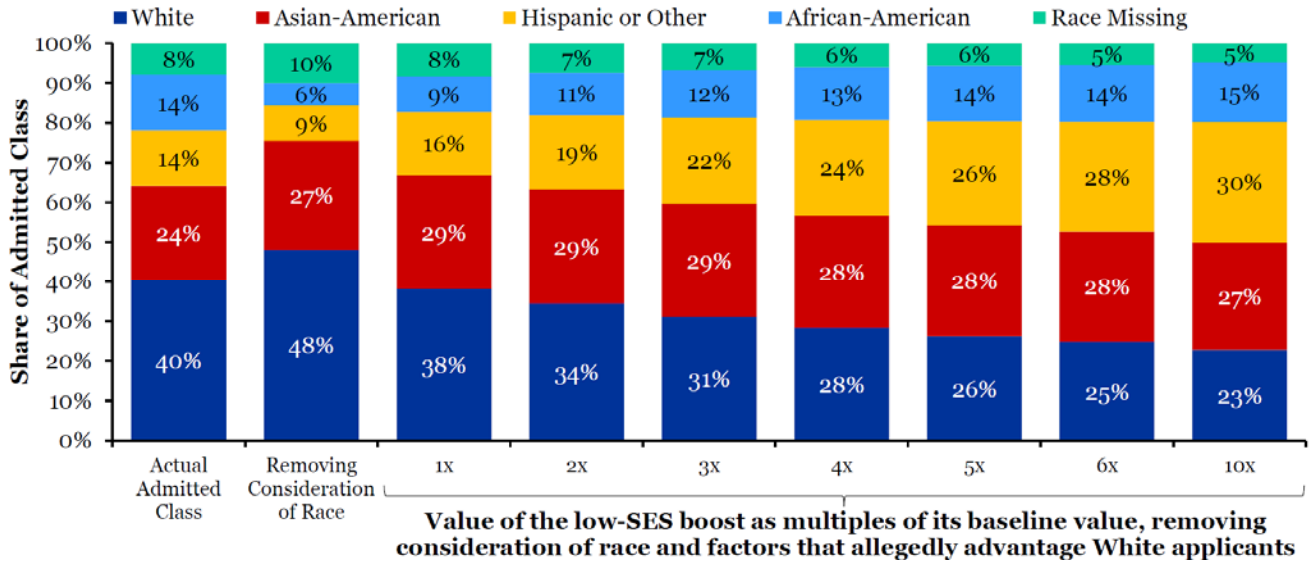
disadvantaged applicants. I find that even if Harvard's recruiting efforts were to double the number of applicants flagged as disadvantaged (and even if those new applicants were of the same quality as current applicants who are disadvantaged), the set of simulated practices would not produce a class both as diverse *and* as high-quality as the one Harvard currently admits.

262. Under the unrealistic assumption that Harvard could actually double the size of its pool of disadvantaged applicants through increased recruiting, it would need to give less of an advantage to low-SES applicants than in prior simulations in order to obtain a proportion of AHO students comparable to that of the current student body (Exhibit 44 and Exhibit 45). But even taken together, *all* of the race-neutral strategies would fail to generate a proportion of African-American students comparable to that of the current class without a very significant preference for low-SES students.

263. A class with a share of AHO students comparable to that of the current class (the 2x bar in Exhibit 44) would exhibit an expected 17% decline in the fraction of students with top academic ratings, as well as declines in average SAT and ACT scores and a large decline in top-rated athletes. Attaining a proportion of African-American students comparable to that of the current class (the 5x bar in Exhibit 44) would be associated with a decline in average SAT scores, ACT scores, and GPAs, and more than a 26% decline in the fraction of applicants with academic ratings of 1 or 2. It would also be associated with a decline in the fraction of applicants with top extracurricular and personal ratings. The number of athletic recruits would plummet, as would the representation of lineage students (Exhibit 46). In addition, as in previous simulations, the financial need of the class would increase a great deal, potentially generating substantial costs to Harvard (Exhibit 47).

Exhibit 44

Doubling the number of disadvantaged applicants in conjunction with other race-neutral policies: Racial composition



Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, standardized test scores, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000. Further, the number of disadvantaged applicants is doubled.

Exhibit 45

Doubling the number of disadvantaged applicants in conjunction with other race-neutral policies: Changes in racial composition

Race	Actual Admitted Class	Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants, Change from Actual Class: 1x Low-SES Boost	2x Low-SES Boost	3x Low-SES Boost	4x Low-SES Boost	5x Low-SES Boost	6x Low-SES Boost	10x Low-SES Boost
1. **White**	676	-35	-97	-154	-201	-236	-259	-295
2. **Asian-American**	402	+79	+80	+78	+74	+69	+65	+55
3. **Hispanic or Other**	233	+33	+83	+131	+173	+206	+230	+276
4. **African-American**	234	-82	-56	-32	-13	-0	+8	+18
5. **Race Missing**	134	+4	-9	-22	-32	-39	-44	-53

Race	Actual Admitted Class	Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants, % Change from Actual Class: 1x Low-SES Boost	2x Low-SES Boost	3x Low-SES Boost	4x Low-SES Boost	5x Low-SES Boost	6x Low-SES Boost	10x Low-SES Boost
1. **White**	40%	-5%	-14%	-23%	-30%	-35%	-38%	-44%
2. **Asian-American**	24%	+20%	+20%	+19%	+18%	+17%	+16%	+14%
3. **Hispanic or Other**	14%	+14%	+36%	+56%	+74%	+88%	+99%	+118%
4. **African-American**	14%	-35%	-24%	-14%	-6%	-0%	+3%	+7%
5. **Race Missing**	8%	+3%	-7%	-16%	-24%	-29%	-33%	-40%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, standardized test scores, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000. Further, the number of disadvantaged applicants is doubled.

Exhibit 46

Doubling the number of disadvantaged applicants in conjunction with other race-neutral policies: Changes in class quality

		Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants					
		1x Low-SES Boost		2x Low-SES Boost		3x Low-SES Boost	
Outcome Measures	**Actual Admitted Class** [A]	**Predicted Value** [B]	**% Change** ([B]-[A])/[A]	**Predicted Value** [C]	**% Change** ([C]-[A])/[A]	**Predicted Value** [D]	**% Change** ([D]-[A])/[A]
Race							
1. White	676	641	-5%	579	-14%	522	-23%
2. Asian-American	402	481	+20%	482	+20%	480	+19%
3. Hispanic or Other	233	266	+14%	316	+36%	364	+56%
4. African-American	234	152	-35%	178	-24%	202	-14%
5. Race Missing	134	138	+3%	125	-7%	112	-16%
Academic							
6. Average Composite SAT Score	2244	2200	-2%	2171	-3%	2142	-5%
7. Average Composite ACT Score	33.1	32.8	-1%	32.5	-2%	32.1	-3%
8. Average Converted GPA	77.0	76.7	-0.3%	76.6	-0.5%	76.4	-1%
9. Average Academic Index	228	226	-1%	224	-2%	222	-3%
Fraction with Profile Rating of 1 or 2							
10. Academic	76%	70%	-7%	63%	-17%	56%	-26%
11. Extracurricular	62%	65%	+5%	62%	-1%	57%	-9%
12. Personal	71%	75%	+6%	73%	+3%	69%	-3%
13. Athletic	27%	20%	-24%	19%	-27%	18%	-31%
Applicant Characteristics							
14. Number of Lineage Students	259	107	-59%	83	-68%	60	-77%
15. Number of Double Lineage Students	72	24	-67%	18	-75%	13	-82%
16. Number of Recruited Athletes	180	94	-48%	93	-48%	92	-49%
17. Number of Children of Harvard Faculty and Staff	44	20	-54%	16	-64%	12	-74%
18. Number of Students on Dean's and Director's Interest Lists	**Redacted**						
19. Number of Female Students	839	865	+3%	869	+4%	871	+4%

Concentration							
20. Social Sciences	25%	25%	-0.3%	25%	-0.4%	24%	-2%
21. Humanities	15%	14%	-3%	14%	-6%	13%	-10%
22. Biological Sciences	21%	23%	+6%	23%	+10%	24%	+14%
23. Physical Science	7%	8%	+5%	8%	+3%	7%	-0.5%
24. Engineering	13%	13%	-0.3%	13%	+0.3%	13%	+3%
25. Computer Science	6%	6%	-8%	6%	-12%	5%	-14%
26. Mathematics	6%	6%	-0.5%	6%	-2%	6%	-3%
27. Unspecified	7%	6%	-9%	6%	-6%	7%	-3%
Geography							
28. Number Rural	59	74	+25%	81	+38%	90	+52%
29. Number in Northeast	694	665	-4%	642	-8%	617	-11%
30. Number in Midwest	207	238	+15%	232	+12%	228	+10%
31. Number in South	379	362	-4%	371	-2%	382	+1%
32. Number in West	399	414	+4%	434	+9%	452	+13%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, standardized test scores, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000. Further, the number of disadvantaged applicants is doubled.

Exhibit 47

Doubling the number of disadvantaged applicants in conjunction with other race-neutral policies: Changes in financial need

		Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants					
		1x Low-SES Boost		**2x Low-SES Boost**		**3x Low-SES Boost**	
Socioeconomic Status	**Actual Admitted Class** [A]	**Predicted Value** [B]	**% Change** ([B]-[A])/[A]	**Predicted Value** [C]	**% Change** ([C]-[A])/[A]	**Predicted Value** [D]	**% Change** ([D]-[A])/[A]
1. Number First Generation College	120	309	+157%	426	+255%	542	+352%
2. Number Disadvantaged	297	773	+160%	980	+230%	1168	+293%
3. Number with Fee Waiver	309	713	+131%	920	+198%	1110	+259%
4. Number with Financial Aid	1102	1332	+21%	1415	+28%	1489	+35%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, standardized test scores, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000. Further, the number of disadvantaged applicants is doubled.

7.3.6. Place-based policies like "percent plans"

7.3.6.1. Place based policies would be difficult to implement

264. Another race-neutral tool for increasing racial diversity identified in the literature is the use of "place-based" admission policies. SFFA and Mr. Kahlenberg both advocate the use of place-based admissions. SFFA's Complaint asserts that Harvard could use place-based preferences to take advantage of community-based homogeneity in race—that is, residential segregation—fostering a diverse class without using race as a factor in admissions. SFFA suggests Harvard could use a "percent plan" like the "top ten percent rule" employed by the University of Texas, under which admission at a University of Texas school is available to the top ten percent of graduating seniors at each public high school in the state. SFFA and Mr. Kahlenberg also suggest that Harvard could admit the top students from each ZIP code.[200] For example, Mr. Kahlenberg simulates a model of admissions based on admitting an equal number of applicants from each of 33 College Board neighborhood "clusters."[201]

265. For at least two reasons, the use of place-based practices like these would likely be impracticable for Harvard. First, place-based practices generally rely on quantitative formulas to determine which student is the "best" in a given high school, neighborhood, or other geographic unit. As discussed earlier, however, I understand that Harvard believes strongly in the importance of a whole-person review that examines the many and varied types of excellence that applicants can bring to campus. Students admitted to Harvard are not all the "best" in the same way; Harvard considers them to be the "best" in many different ways, which an algorithm could not capture. To determine which student in each high school or ZIP code was the "best" on the broader array of dimensions considered in its whole-person process, Harvard would have to apply its whole-person process at the outset, simply to identify which "top" student to admit. That would be extraordinarily labor-intensive, particularly given that any plan like this would likely draw a sharply increased number of applicants. And it would also ignore the fact that Harvard pursues excellences of many kinds, not excellence on a single dimension. Even within the whole-person process, that is, there is no such thing as a "best" student; there are, rather, students who excel in many different ways.

[200] Note that these types of place-based polices rely on allocating slots to students from different geographies (or types of geographies); these policies differ from simply considering an applicant's high school and neighborhood as one of many pieces of information in a whole-person admissions process.

[201] There are 33 College Board neighborhood clusters, but Mr. Kahlenberg creates an extra cluster for applicants missing College Board data, and combines a small cluster with the extra "cluster" of applicants missing College Board data.

266. Second, there are many times more high schools, cities, and ZIP codes represented in the applicant pool than there are slots in the incoming class. Harvard does not serve a limited geography; its reach is national and global. Even if Harvard admitted only the "top" student from each U.S. high school represented in its applicant pool—and even if it were simple to identify the "top" student, which it is not, for the reason discussed above[202]—the result would be a class four to five times larger than Harvard's actual class. The class of 2019, for example, had 1,719 admitted students from domestic high schools—but over 7,500 U.S. high schools were represented in the applicant pool, spanning over 4,000 cities and towns (see Exhibit 48).[203] Reserving even *one* slot per high school is not feasible for Harvard, even if one limits the exercise to the subset of U.S. high schools currently represented in Harvard's applicant pool. As noted in Exhibit 48, there are over 41,000 high schools across the United States, and more than 33,000 ZIP codes. Moreover, if Harvard were to publicize a policy to offer admission to the top student from each high school or ZIP code, it would likely see a massive increase in the number of applications, generating substantial costs to review them.

267. In light of the sheer number of schools and geographic locations represented in its applicant pool, Harvard would need to either draw randomly from among top students across places, or combine a place-based percent plan with additional algorithmic screens for desirable characteristics (which would deprive it of the chance to identify dimensions of achievement that are not easily quantified) or a whole-person review applied to the entire pool of "top students."

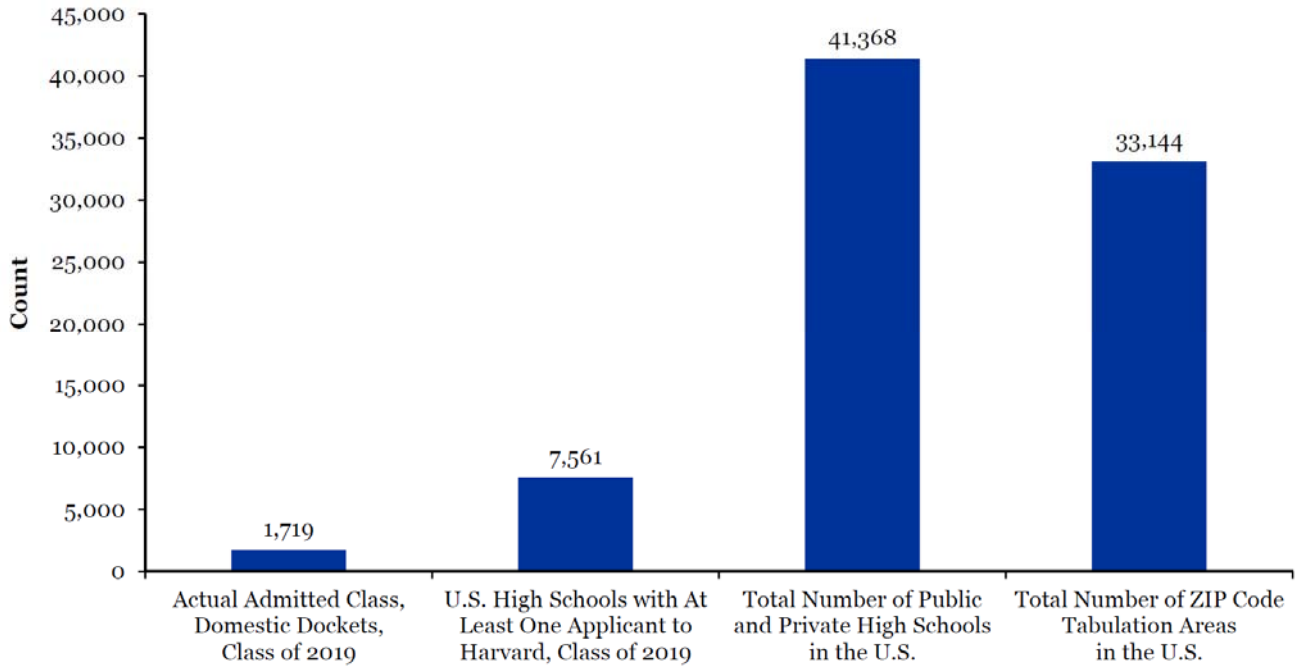
268. Crucially, any such approach would preclude Harvard from admitting multiple candidates from the same high school or neighborhood, even though, say, the tenth student Harvard admits from a given high school or neighborhood might well bring more to campus than the top student in some other high school or neighborhood.

[202] Mr. Kahlenberg ranks applicants within a cluster based on their predicted probability of admission, computed using his full admissions model. This is hardly practical: his proposal would effectively entail conducting the entire Harvard admissions process, then ranking the entire applicant pool within geographies. Currently, officers do not rank all applicants in the pool, nor is there a workable method for selecting the "best" student from a high school or ZIP code when Harvard seeks excellence of so many kinds.

[203] There are 4,006 unique geographic locations represented among applicants to the class of 2019, as determined by applicants' high school location. These geographic locations vary in size and include cities, towns, neighborhoods, and unincorporated communities. Because many cities and towns contain more than one ZIP code, there are likely far more than 4,006 ZIP codes represented in the Harvard applicant pool. See workpaper.

Exhibit 48

There are far more high schools and ZIP codes than slots in Harvard's admitted class



Source: Augmented Arcidiacono Data; National Center for Education Statistics; U.S. Census Data

Note: Sample consists of all applicants to the class of 2019 on domestic dockets in Prof. Arcidiacono's corrected expanded sample. Total number of public and private high schools in 2013 – 2014 (i.e., classes of 2017 – 2018) includes schools with both elementary and secondary grades. ZIP Code Tabulation Areas are representations of ZIP code service areas created by the U.S. Census Bureau to represent statistical data from censuses and surveys. Total number of ZIP Code Tabulation Areas in 2016 is shown

269. Notwithstanding the infeasibility of the practices discussed above, I examined how the racial diversity and other characteristics of Harvard's admitted class would be expected to change if Harvard implemented a place-based admission policy that focused on "top students" from each high school.[204] As I show below, such a practice would not be effective in both fostering racial diversity and preserving class quality.

270. A primary aim of place-based admissions practices is to use the reality of residential segregation to increase representation from underrepresented groups. To that end, in addition to studying the characteristics of all top students, I also examine the characteristics of all top students coming from public high schools (the traditional target for percent plans), low-income high schools

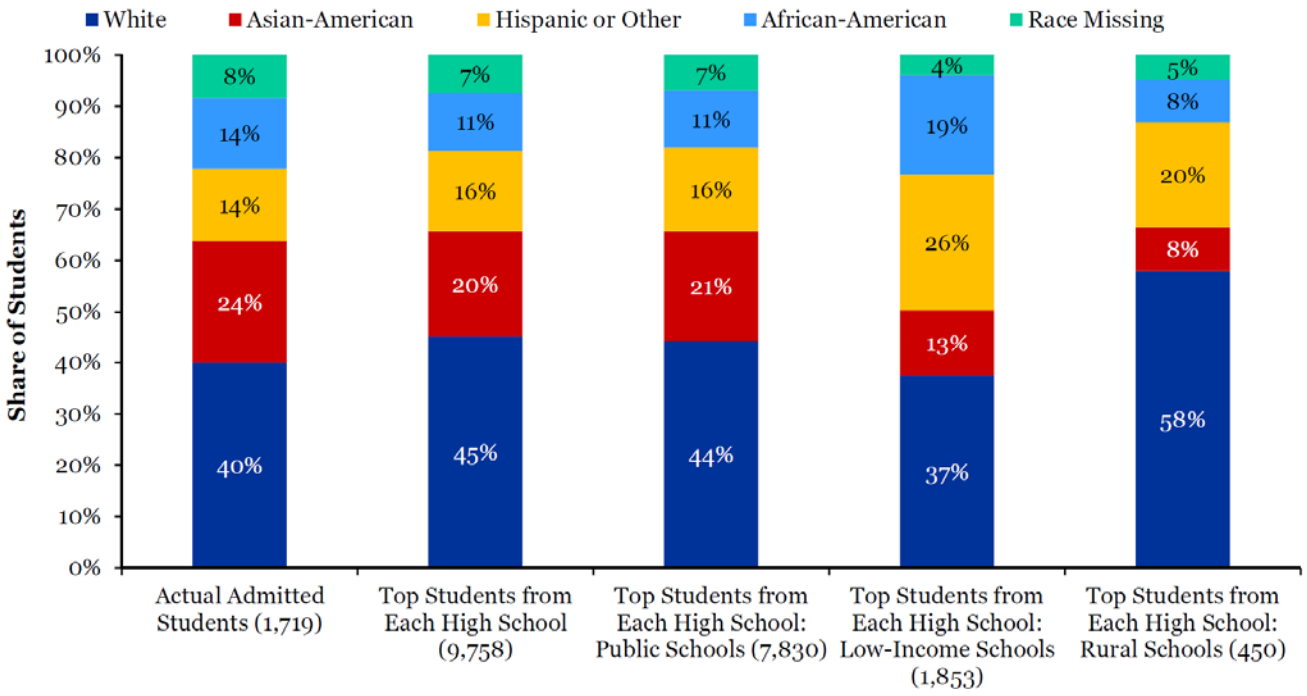
[204] For the purpose of this exercise, I rank all students within a high school by the sum of their profile ratings, and refer to the pool of top-ranked students as "top students." This is a parsimonious way to rank students while still paying some attention to Harvard's desire for whole-person evaluation, but it is obviously a crude way of identifying the "top" student. The exercise of ranking "top" students in this way does not suggest that doing so would actually fulfill Harvard's educational objective of admitting students who embody many and varied forms of excellence.

(defined as high schools with a median household income less than $65,000), and rural high schools.

271. As shown in Exhibit 49, the pool of top students at all high schools contains roughly the same fraction of AHO applicants as the actual pool of admitted students, but somewhat fewer Asian-American applicants. Top students from public schools are similarly racially diverse. Top students from low-income schools are heavily AHO. In contrast, the pool of top students from rural schools is predominantly White, with few Asian-American students. These figures suggest that filling some (or all) of Harvard's class with top students from United States high schools, public high schools, or low-income high schools could in principle help produce a racially diverse class. Tapping top rural talent is unlikely to foster racial diversity.

Exhibit 49

Racial composition of top students, applicants to the class of 2019



Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of all applicants to the class of 2019 on domestic dockets in Prof. Arcidiacono's corrected expanded sample. Students are ranked based on a sum of the four profile ratings: academic, athletic, extracurricular, and personal. The top students are selected based on rank within each school, allowing for ties. Low-income schools are defined as schools with average median income less than or equal to $65,000.

272. However, admitting students in this manner would likely cause a sharp decline in the quality of the admitted class. As evidenced by Exhibit 50, the pools of top students in Harvard's data—whether from all high schools, public schools, low-income schools, or rural schools—have markedly lower profile ratings (on all four dimensions), lower SAT and ACT scores, and lower

Academic Index values than the current pool of admitted students. The main reason for this decline in quality is that, by admitting only the top student from each school, Harvard is forced to replace a large number of excellent applicants from the most competitive high schools in the country with top students from high schools that are substantially weaker.

273. Taken together, this evidence indicates that place-based admissions practices that reserve slots for top performers at each high school could generate racial diversity, but at the expense of the quality of the admitted class.

Exhibit 50

Percent plans would likely decrease the quality of the admitted class

Outcome Measures	Actual Admitted Class [A]	Top students, all schools (9,758) Average [B]	Top students, all schools (9,758) % Difference ([B]-[A]) / [A]	Top students, public schools (7,830) Average [C]	Top students, public schools (7,830) % Difference ([C]-[A]) / [A]
Academic					
1. Average Composite SAT Score	2242	2082	-7%	2071	-8%
2. Average Composite ACT Score	33	32	-4%	32	-5%
3. Average Converted GPA	76.9	76.4	-1%	76.6	-0.5%
4. Average Academic Index	228	218	-4%	218	-4%
Fraction with Profile Rating of 1 or 2					
5. Academic	75%	49%	-35%	48%	-37%
6. Extracurricular	62%	33%	-47%	33%	-48%
7. Personal	71%	30%	-58%	29%	-59%
8. Athletic	27%	18%	-34%	17%	-38%

Outcome Measures	Actual Admitted Class [A]	Top students, low-income schools (1,853) Average [B]	Top students, low-income schools (1,853) % Difference ([B]-[A]) / [A]	Top students, rural schools (450) Average [C]	Top students, rural schools (450) % Difference ([C]-[A]) / [A]
Academic					
9. Average Composite SAT Score	2242	1884	-16%	2032	-9%
10. Average Composite ACT Score	33	29	-11%	31	-6%
11. Average Converted GPA	76.9	75.2	-2%	76.0	-1%
12. Average Academic Index	228	206	-10%	216	-5%
Fraction with Profile Rating of 1 or 2					
13. Academic	75%	20%	-73%	38%	-50%
14. Extracurricular	62%	22%	-65%	23%	-64%
15. Personal	71%	19%	-73%	25%	-65%
16. Athletic	27%	11%	-59%	15%	-45%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of all applicants to the class of 2019 on domestic dockets in Prof. Arcidiacono's corrected expanded sample. Students are ranked based on a sum of the four profile ratings: academic, athletic, extracurricular, and personal. The top students are selected based on rank within each school, allowing for ties. Low-income schools are defined as schools with average median income less than or equal to $65,000..

7.3.6.2. Implementing neighborhood cluster-based admissions in conjunction with other race-neutral policies

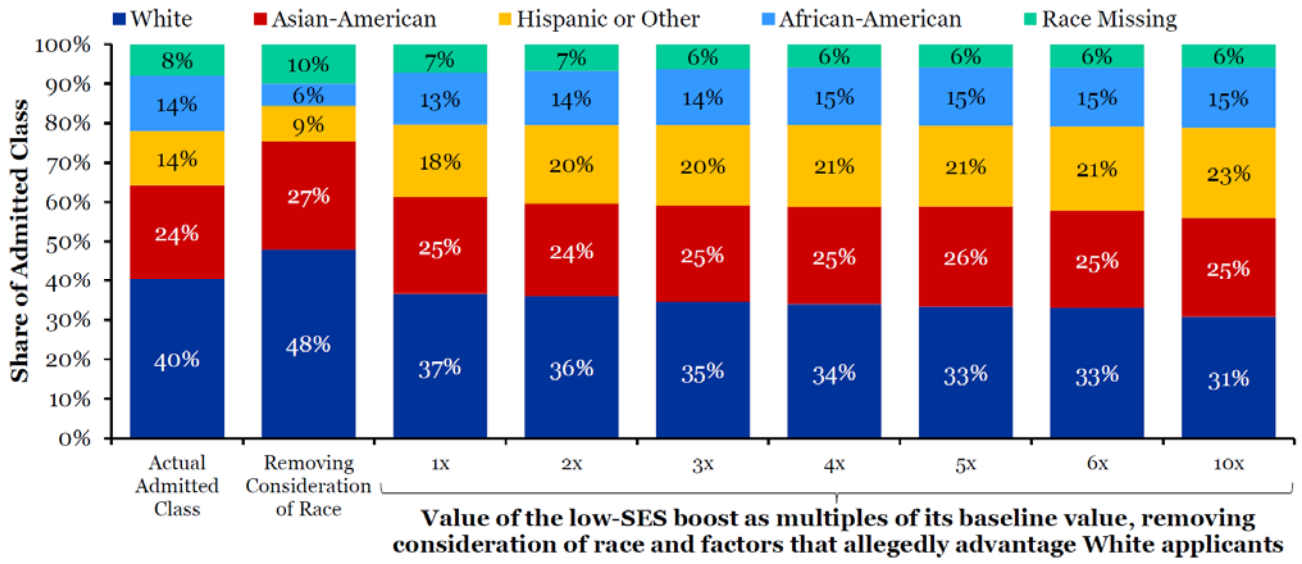
274. In his report, Mr. Kahlenberg includes simulations in which Harvard abandons its whole-person admissions process and instead admits an equal number of students from each of the College Board's neighborhood clusters. In the same simulations, Mr. Kahlenberg also gives disadvantaged students an admissions preference, and assumes that Harvard could double its pool of disadvantaged applicants through outreach and recruiting.

275. Building on the simulations above, I, too, consider how the admitted class would change under such a regime. As in Mr. Kahlenberg's report, I rank students within a cluster based on their estimated probability of admission. I generate the ranking using a model of admissions in which Harvard admissions officers (1) do not consider race, lineage status, whether an applicant is an athletic recruit, whether an applicant is a child of Harvard faculty or staff, or whether an applicant is on the Dean's or Director's interest list, (2) afford a preference to low-SES applicants as discussed in Section 7.3.3 above, and (3) eliminate consideration of standardized test scores. Furthermore, I assume that through increased recruiting and outreach Harvard could double the number of disadvantaged applicants in its pool, although that assumption is unrealistic for the reasons discussed above.

276. As suggested by my findings in Section 7.3.6.1, place-based admissions could help foster racial diversity, but only at a steep cost to the quality of the admitted class. Each bar in Exhibit 51 depicts the racial composition of the expected class under a neighborhood-based admissions policy for a given boost for low-SES applicants. Recall that in addition to using cluster-based admissions, I have already eliminated consideration of test scores, and I am also assuming Harvard could double its pool of disadvantaged applicants through outreach; as a result, a lesser low-SES boost is required to attain a given level of AHO representation. Even in this conservative scenario, however, generating a proportion of African-American students comparable to that of the current class requires a significant low-SES boost. This combination of practices would be expected to increase the proportion of Hispanic students relative to the current class. The proportion of Asian-American students would stay relatively constant. The fraction of White students also falls in this simulation.

Exhibit 51

Admitting an equal number of students across neighborhood clusters, in conjunction with other race-neutral policies: Racial composition



Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, standardized test scores, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000. Further, the number of disadvantaged applicants is doubled. Applicants are ranked in descending order of admission index within each neighborhood cluster and an approximately equal number of applicants are admitted from each cluster to fill the class.

Exhibit 52

Admitting an equal number of students across neighborhood clusters, in conjunction with other race-neutral policies: Changes in racial composition

Race	Actual Admitted Class	Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants, Change from Actual Class: 1x Low-SES Boost	2x Low-SES Boost	3x Low-SES Boost	4x Low-SES Boost	5x Low-SES Boost	6x Low-SES Boost	10x Low-SES Boost
1. **White**	676	-62	-72	-96	-107	-117	-122	-159
2. **Asian-American**	402	+12	-4	+11	+16	+27	+16	+21
3. **Hispanic or Other**	233	+77	+101	+110	+117	+113	+124	+150
4. **African-American**	234	-14	-5	+4	+10	+13	+17	+24
5. **Race Missing**	134	-13	-20	-29	-36	-36	-35	-36

Race	Actual Admitted Class	Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants, % Change from Actual Class: 1x Low-SES Boost	2x Low-SES Boost	3x Low-SES Boost	4x Low-SES Boost	5x Low-SES Boost	6x Low-SES Boost	10x Low-SES Boost
1. **White**	40%	-9%	-11%	-14%	-16%	-17%	-18%	-24%
2. **Asian-American**	24%	+3%	-1%	+3%	+4%	+7%	+4%	+5%
3. **Hispanic or Other**	14%	+33%	+43%	+47%	+50%	+48%	+53%	+64%
4. **African-American**	14%	-6%	-2%	+2%	+4%	+6%	+7%	+10%
5. **Race Missing**	8%	-10%	-15%	-22%	-27%	-27%	-26%	-27%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, standardized test scores, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000. Further, the number of disadvantaged applicants is doubled. Applicants are ranked in descending order of admission index within each neighborhood cluster and an approximately equal number of applicants are admitted from each cluster to fill the class.

277. The racial diversity attained through the set of practices simulated in Exhibit 51 and Exhibit 52 comes at a high cost. Exhibit 53 depicts the simulated change in class composition associated with using a cluster-based admissions process in conjunction with other race-neutral alternatives. Attaining a proportion of AHO students comparable to that of the current class (the 1x results) is associated with a 17% decline in the fraction of applicants with top academic ratings. Generating a proportion of African-American students comparable to that of the current class is associated with more than a 23% decline in the fraction of admitted students with top academic ratings. In either scenario, the number of recruited athletes and lineage students declines sharply (Exhibit 53), and the financial need of admitted students increases (Exhibit 54).

Exhibit 53

Admitting an equal number of students across neighborhood clusters, in conjunction with other race-neutral policies: Changes in class quality

		Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants					
		1x Low-SES Boost		2x Low-SES Boost		3x Low-SES Boost	
Outcome Measures	Actual Admitted Class [A]	Predicted Value [B]	% Change ([B]-[A])/[A]	Predicted Value [C]	% Change ([C]-[A])/[A]	Predicted Value [D]	% Change ([D]-[A])/[A]
Race							
1. White	676	614	-9%	604	-11%	580	-14%
2. Asian-American	402	414	+3%	398	-1%	413	+3%
3. Hispanic or Other	233	310	+33%	334	+43%	343	+47%
4. African-American	234	220	-6%	229	-2%	238	+2%
5. Race Missing	134	121	-10%	114	-15%	105	-22%
Academic							
6. Average Composite SAT Score	2244	2163	-4%	2149	-4%	2136	-5%
7. Average Composite ACT Score	33.1	32.5	-2%	32.2	-3%	32.0	-3%
8. Average Converted GPA	77.0	76.5	-1%	76.5	-1%	76.3	-1%
9. Average Academic Index	228	223	-2%	222	-2%	221	-3%
Fraction with Profile Rating of 1 or 2							
10. Academic	76%	63%	-17%	59%	-23%	54%	-29%
11. Extracurricular	62%	60%	-3%	56%	-10%	53%	-15%
12. Personal	71%	73%	+3%	70%	-1%	67%	-6%
13. Athletic	27%	20%	-25%	20%	-24%	19%	-30%
Applicant Characteristics							
14. Number of Lineage Students	259	67	-74%	61	-76%	47	-82%
15. Number of Double Lineage Students	72	13	-82%	13	-82%	11	-85%
16. Number of Recruited Athletes	180	94	-48%	95	-47%	94	-48%
17. Number of Children of Harvard Faculty and Staff	44	12	-73%	12	-73%	10	-77%
18. Number of Students on Dean's and Director's Interest Lists	Redacted						
19. Number of Female Students	839	846	+1%	843	+0.5%	843	+0.5%

Concentration							
20. Social Sciences	25%	24%	-3%	24%	-3%	24%	-4%
21. Humanities	15%	14%	-7%	13%	-10%	13%	-9%
22. Biological Sciences	21%	22%	+4%	23%	+9%	23%	+10%
23. Physical Science	7%	8%	+11%	9%	+16%	8%	+12%
24. Engineering	13%	13%	+3%	13%	0.00%	13%	+3%
25. Computer Science	6%	5%	-20%	5%	-21%	5%	-19%
26. Mathematics	6%	7%	+12%	7%	+4%	6%	-3%
27. Unspecified	7%	7%	+1%	7%	+3%	7%	+4%
Geography							
28. Number Rural	59	130	+120%	133	+125%	137	+132%
29. Number in Northeast	694	590	-15%	592	-15%	593	-15%
30. Number in Midwest	207	279	+35%	274	+32%	279	+35%
31. Number in South	379	435	+15%	431	+14%	438	+16%
32. Number in West	399	375	-6%	382	-4%	369	-8%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, standardized test scores, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000. Further, the number of disadvantaged applicants is doubled. Applicants are ranked in descending order of admission index within each neighborhood cluster and an approximately equal number of applicants are admitted from each cluster to fill the class.

Exhibit 54

Admitting an equal number of students across neighborhood clusters, in conjunction with other race-neutral policies: Changes in financial need

		Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants					
		1x Low-SES Boost		2x Low-SES Boost		3x Low-SES Boost	
Socioeconomic Status	Actual Admitted Class [A]	Predicted Value [B]	% Change ([B]-[A])/[A]	Predicted Value [C]	% Change ([C]-[A])/[A]	Predicted Value [D]	% Change ([D]-[A])/[A]
1. Number First Generation College	120	344	+187%	427	+256%	530	+342%
2. Number Disadvantaged	297	906	+205%	1047	+253%	1176	+296%
3. Number with Fee Waiver	309	853	+176%	1000	+224%	1127	+265%
4. Number with Financial Aid	1102	1431	+30%	1471	+33%	1507	+37%

Source: Augmented Arcidiacono Data; College Board Cluster Data; U.S. Census Data

Note: Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's corrected expanded sample who are in my preferred year-by-year regression model. Simulation eliminates consideration of race, lineage status, recruited-athlete status, whether an applicant's parents are Harvard faculty and staff, whether the applicant appears on the Dean's or Director's interest list, standardized test scores, and the proportion of the applicant's high school and neighborhood that is African-American, Hispanic, and White. In addition, recruited athletes are reassigned to rating combinations in the regression sample that contain the next highest athletic rating. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admission index. The value is equal to 0.5 multiplied by a given integer multiplier, multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to $65,000. Further, the number of disadvantaged applicants is doubled. Applicants are ranked in descending order of admission index within each neighborhood cluster and an approximately equal number of applicants are admitted from each cluster to fill the class.

7.3.7. Increasing financial aid

278. Mr. Kahlenberg also identifies generous financial aid as a way to expand racial diversity, on the theory that some talented low-SES applicants, many of whom are AHO, do not apply to or matriculate at Harvard because of expected costs but *would* apply or matriculate if Harvard were more affordable.[205] But available evidence suggests that increasing aid beyond Harvard's current generous levels would not produce additional racial diversity among applicants or matriculants.

279. Harvard already offers exceptionally generous financial aid. Its financial aid program is designed to "ensure that students admitted to Harvard are not prevented from matriculating due to their financial circumstances," and "to ensure that Harvard will be affordable to every student."[206] "Currently, Harvard expects no parental contribution for students from families with typical assets and annual incomes below $65,000. Families with typical assets and incomes between $65,000 and

[205] Kahlenberg Report, pp. 29–31.

[206] Second Interrogatory Response, p. 16.

$150,000 are generally expected to contribute between 0–10% of their income, and Harvard does not consider the family's home equity in calculating family resources."[207]

280. These policies are generous enough to make Harvard more affordable to low-income applicants than many public institutions. Harvard estimates that "[n]inety percent of American families would pay the same or less to send their children to Harvard as they would a state school."[208] When the New York Times ranked 171 top public and private colleges based on the number of middle- and low-income students served and the net amount charged to those students, Harvard came in tenth, ahead of all of its Ivy League peers. Based on net-price calculations for middle-income students only, Harvard came in second, behind only Stanford.[209] Harvard's current threshold for zero parental contribution is as generous as or more generous than the limits at Ivy League peers and Stanford.[210] Approximately 70% of African-American households and more than 60% of all Hispanic households are already eligible for zero parental contribution.[211]

281. Harvard's current financial aid program is the culmination of a decade of financial aid initiatives, summarized in Exhibit 55. These staggered changes in the aid thresholds provide a natural experiment: they allow me to assess whether historical increases in financial aid drew in AHO applicants, contributed to an increase in the share of AHO admitted students, or helped boost matriculation of AHO admitted students. These historical patterns can also shed light on what might happen to the pools of applicants and admitted students if Harvard were to expand its financial aid

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[207] Second Interrogatory Response, p. 16.

[208] Harvard College, Financial Aid Fact Sheets, available at https://college.harvard.edu/financial-aid/how-aid-works/fact-sheet, accessed December 12, 2017.

[209] New York Times, "Top Colleges Doing the Most for the American Dream," available at https://www.nytimes.com/interactive/2017/05/25/sunday-review/opinion-pell-table.html, accessed November 19, 2017 ("The ranking is based on a combination of the number of lower-and middle-income students that a college enrolls and the price it charges these students. The top of the ranking is dominated by campuses in the University of California system, while the most diverse private colleges include Amherst, Pomona, Harvard and Vassar.").

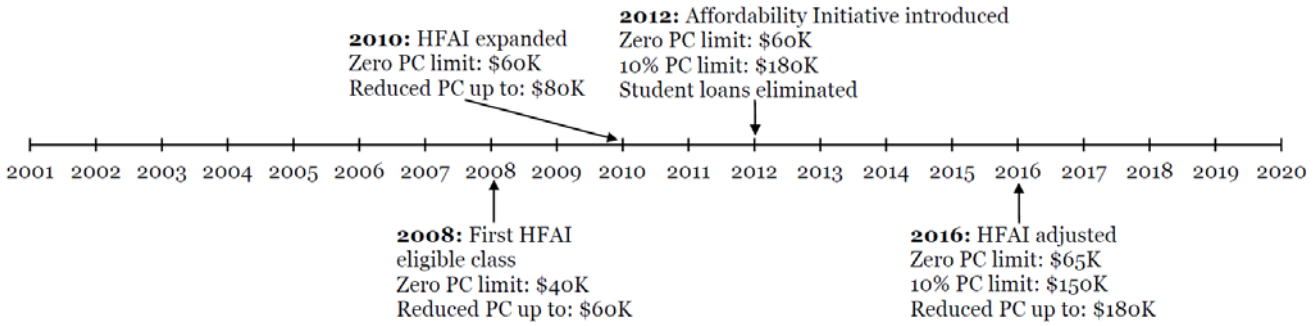
[210] While Dartmouth offers free tuition for families whose total income is $100,000 or less, the other Ivy League institutions and Stanford cover all educational costs (including tuition, room, board, books, etc.) in their aid for families falling at or below their zero parental contribution thresholds. Penn Student Registration & Financial Services, "A Look at the Facts," available at http://www.sfs.upenn.edu/paying/paying-pro-look-at-the-facts.htm, accessed December 5, 2017; Brown University, "General Questions," available at https://www.brown.edu/about/administration/financial-aid/general-questions, accessed December 5, 2017; Columbia University, "How Aid Works," available at https://cc-seas.financialaid.columbia.edu/how/aid/works, accessed December 5, 2017; Cornell University, "Financial Aid, Financial Aid Initiative," available at https://finaid.cornell.edu/cost-attend/financial-aid-initiatives, accessed December 5, 2017; Yale University, "Financial Aid In-Depth," available at https://admissions.yale.edu/financial-aid-prospective-students, accessed December 5, 2017; Princeton University, "How Princeton's Aid Program Works," available at https://admission.princeton.edu/cost-aid/how-princetons-aid-program-works, accessed December 5, 2017; Stanford University, "How Aid Works," available at https://financialaid.stanford.edu/undergrad/how/parent.html, accessed December 5, 2017; Dartmouth College, "How Aid Works," available at http://admissions.dartmouth.edu/financial-aid/how-aid-works/how-much-help-will-i-get, accessed December 5, 2017.

[211] See workpaper based on data from the U.S. Census Bureau, Current Population Survey 2017 Annual Social and Economic Supplement.

offerings further. Surprisingly, Mr. Kahlenberg failed to consider this historical evidence of how his proposed race-neutral alternatives have fared in practice.

Exhibit 55

Timeline of Harvard's changes to financial aid policies, by class

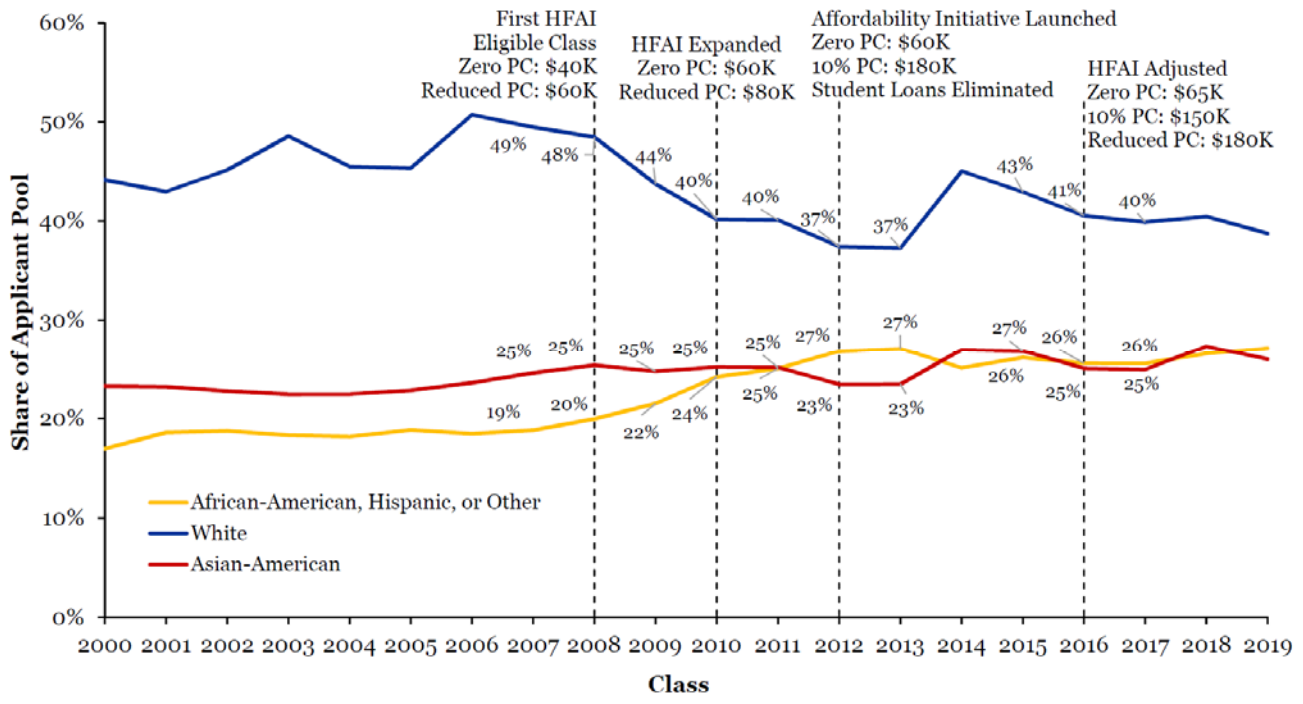


Source: HARV00031667; HARV00016122; HARV00010744; HARV00067792

282. In the following set of exhibits, I examine how three key outcomes have changed as Harvard expanded its financial aid: number of applicants of each race, number of admitted students of each race, and matriculation rates by race. I find that the fraction of AHO applicants (among all applicants) rose and then plateaued as Harvard expanded financial aid (Exhibit 56). Importantly, the most recent expansion of financial aid did not result in an increase in the share of AHO applicants. The fraction of Asian-American applicants rose slightly, while the fraction of applicants who are White fell.

Exhibit 56

Share of African-American, Hispanic, or Other applicants rose, then plateaued, as Harvard expanded financial aid



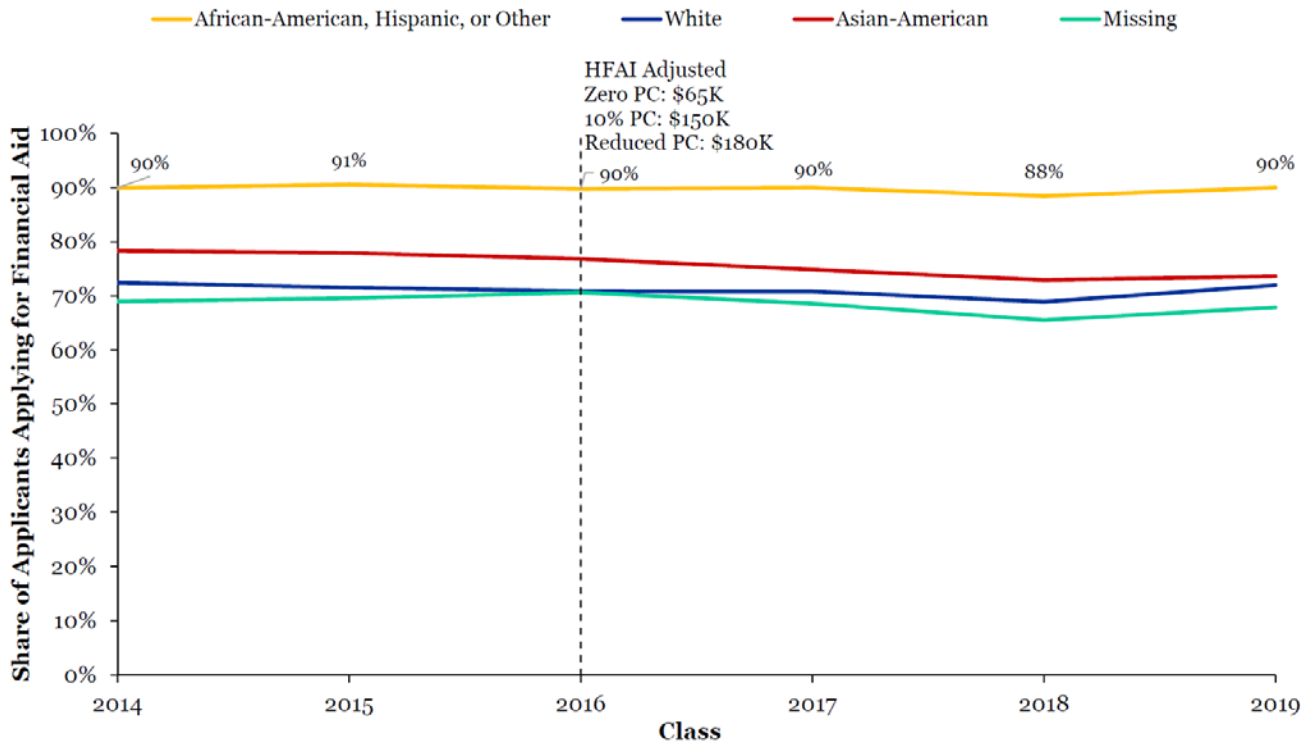
Source: HARV00032509 – HARV00032524; HARV00031667; HARV00016122; HARV00010744; HARV00067792; Augmented Arcidiacono Data

Note: Applicants classified as "Native American / Hawaiian" are grouped with applicants classified as "Other." Data for classes 2018 – 2019 are reconstructed using a methodology that replicates the produced aggregate data for classes 2000 – 2017.

283. The fraction of AHO applicants who applied for financial aid also did not increase after the most recent expansion (Exhibit 57). This suggests that financial aid is not a limiting factor for AHO applicants. This pattern holds for applicants of other races as well.

Exhibit 57

Most recent increase in the threshold for zero parental contribution did not increase fraction of African-American, Hispanic, or Other applicants applying for financial aid



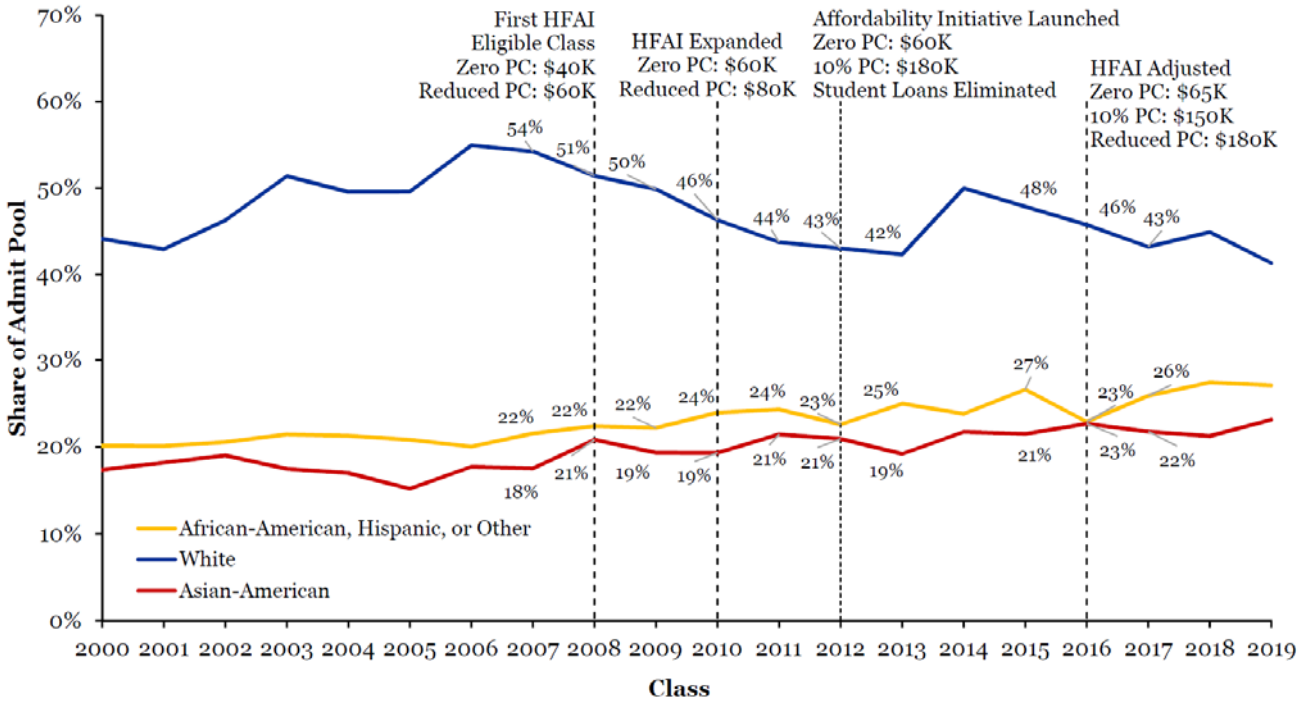
Source: Augmented Arcidiacono Data

Note: Applicants classified as "Native American / Hawaiian" are grouped with applicants classified as "Other." Racial categories are constructed using a methodology that replicates the racial categories in the produced aggregate data.

284. Increases in financial aid were also not closely linked to changes in the fraction of AHO or Asian-American applicants among admitted students (Exhibit 58). The most recent expansion of financial aid for the class of 2016 did not increase the share of admitted students who are AHO. Expansions in financial aid were also not consistently associated with increases in matriculation of AHO admitted students relative to other races (Exhibit 59).

Exhibit 58

Share of African-American, Hispanic, or Other admitted students has risen over time, but not in close step with expansions in financial aid

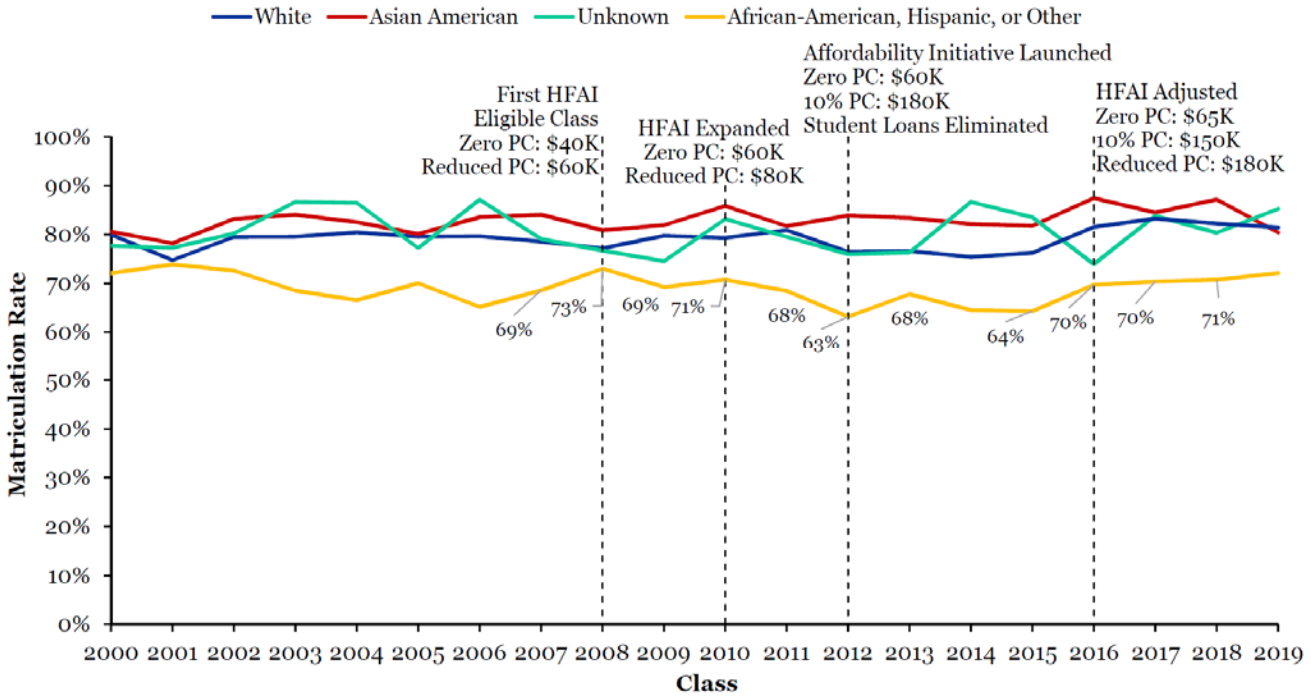


Source: HARV00032509 – HARV00032524; HARV00031667; HARV00016122; HARV00010744; HARV00067792; Augmented Arcidiacono Data

Note: Applicants classified as "Native American / Hawaiian" are grouped with applicants classified as "Other." Data for classes 2018 – 2019 are reconstructed using a methodology that replicates the produced aggregate data for classes 2000 – 2017.

Exhibit 59

Expansions in financial aid did not consistently affect matriculation of African-American, Hispanic, or Other admitted students



Source: HARV00032509 – HARV00032524; HARV00031667; HARV00016122; HARV00010744; HARV00067792; Augmented Arcidiacono Data

Note: Applicants classified as "Native American / Hawaiian" are grouped with applicants classified as "Other." Data for classes 2018 – 2019 are reconstructed using a methodology that replicates the produced aggregate data for classes 2000 – 2017.

285. These results indicate it is unlikely that Harvard would be able to increase its proportion of AHO students (relative to a regime of not considering race) by offering more generous financial aid. Even with Harvard's continuous expansion of its financial aid program, the share of applicants who are AHO has not risen markedly over the past eight years. That is, perhaps, not surprising when one considers the current income distribution in the United States. The vast majority of households in the $60,000–65,000, $65,000–70,000, and $70,000–75,000 income brackets are not AHO, and there are fewer and fewer AHO households as one moves up those brackets. Given the distribution of income by race, incremental expansions in the $65,000 threshold for zero parental contribution are likely to disproportionately attract White applicants, not AHO applicants.[212]

[212] See workpaper based on data from the U.S. Census Bureau, Current Population Survey 2017 Annual Social and Economic Supplement.

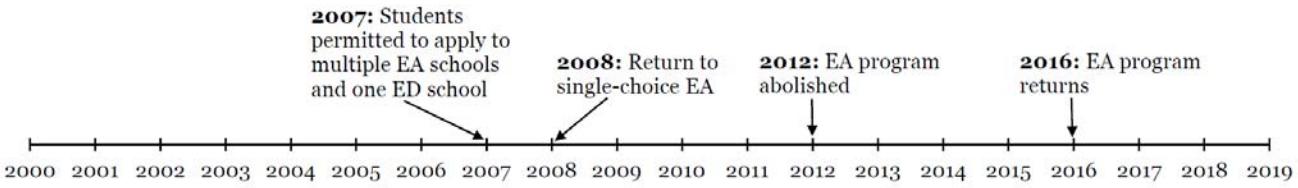
7.3.8. Eliminating Early Action

286. The academic literature and Mr. Kahlenberg suggest that Early Action admissions could potentially privilege applicants with more resources and better college guidance counseling. Because these students are more likely to be White, Mr. Kahlenberg argues that eliminating Early Action could enhance racial diversity at Harvard.[213] This claim is directly testable, because Harvard both eliminated and reinstated Early Action in recent years, allowing researchers to observe the effect of such changes on the pool of applicants and admitted students. Had Mr. Kahlenberg examined this historical evidence, he would have found that Harvard's experience indicates that abolishing Early Action once again is unlikely to increase racial diversity.

287. To assess the effect of abolishing Early Action on racial diversity, I look at the racial composition of Harvard's applicants, admitted students, and matriculants before and after Harvard implemented key changes in its Early Action policy. Exhibit 60 summarizes those changes. Harvard offered some form of Early Action through the class of 2011.[214] Harvard eliminated Early Action for the class of 2012, and then reinstated it for applicants to the class of 2016. Those changes in policy provide a natural experiment to test Mr. Kahlenberg's claim that eliminating Early Action could increase racial diversity at Harvard. I focus on comparing the period during which Harvard abolished Early Action to the more recent period after Harvard reinstated Early Action, as financial aid policies were more similar during these periods than in earlier years.

Exhibit 60

Timeline of Harvard's changes to Early Action policies, by class



Source: HARV00031695

[213] Kahlenberg Report, pp. 42–44; Complaint, pp. 85–86; Julie J. Park and M. Kevin Eagan, "Who Goes Early? A Multi-Level Analysis of Enrolling via Early Action and Early Decision Admissions," *Teachers College Record*, 113(11), 2011; pp. 2345–2373 at pp. 2358, 2365, and 2368; Christopher Avery and Jonathan Levin, "Early Admission at Selective Colleges," *Stanford Institute for Economic Policy Research* No. 08–31 March 2009, pp. 1–36 at p. 4.

[214] In the class of 2007 admissions cycle, Harvard permitted applicants to apply early to multiple institutions, but reverted to single-choice early action for the classes of 2008 to 2011.

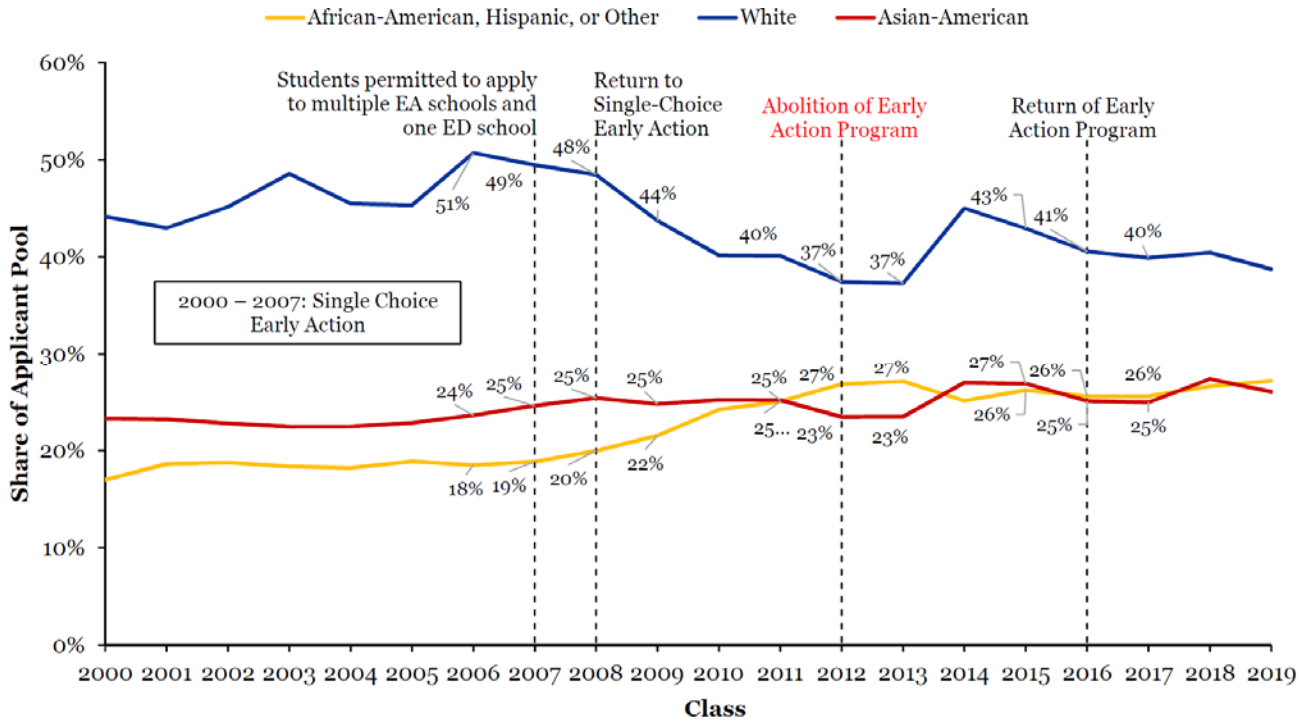
288. I start my analysis by looking at whether reinstating Early Action had an effect on the racial composition of *applicants* (Exhibit 61). As Exhibit 61 shows, the fraction of AHO applicants in the applicant pool rose steadily from the class of 2000 through roughly the class of 2012, when Early Action was abolished. The fraction of AHO applicants then plateaued in more recent years, averaging 26% during the period Early Action was abolished (classes of 2012 – 2015) and 26% after Early Action was reinstated.[215] The fact that reinstating Early Action has not led to a meaningful decrease in the fraction of applicants who are AHO suggests that abolishing Early Action again would not be likely to increase the fraction of AHO students in the applicant pool.

289. The fraction of Asian-American applicants increased a small amount between the classes of 2000 – 2011, dipped slightly during the first two years in which Early Action was abolished (2012 – 2013), then rose again. The share of applicants who are White generally fell throughout the 2000 – 2019 period, jumping only briefly in the class of 2014.

[215] See workpaper.

Exhibit 61

Reinstating Early Action did not have an effect on the share of applicants who are African-American, Hispanic, or Other



Source: HARV00032509 – 24; HARV00031695; Augmented Arcidiacono Data

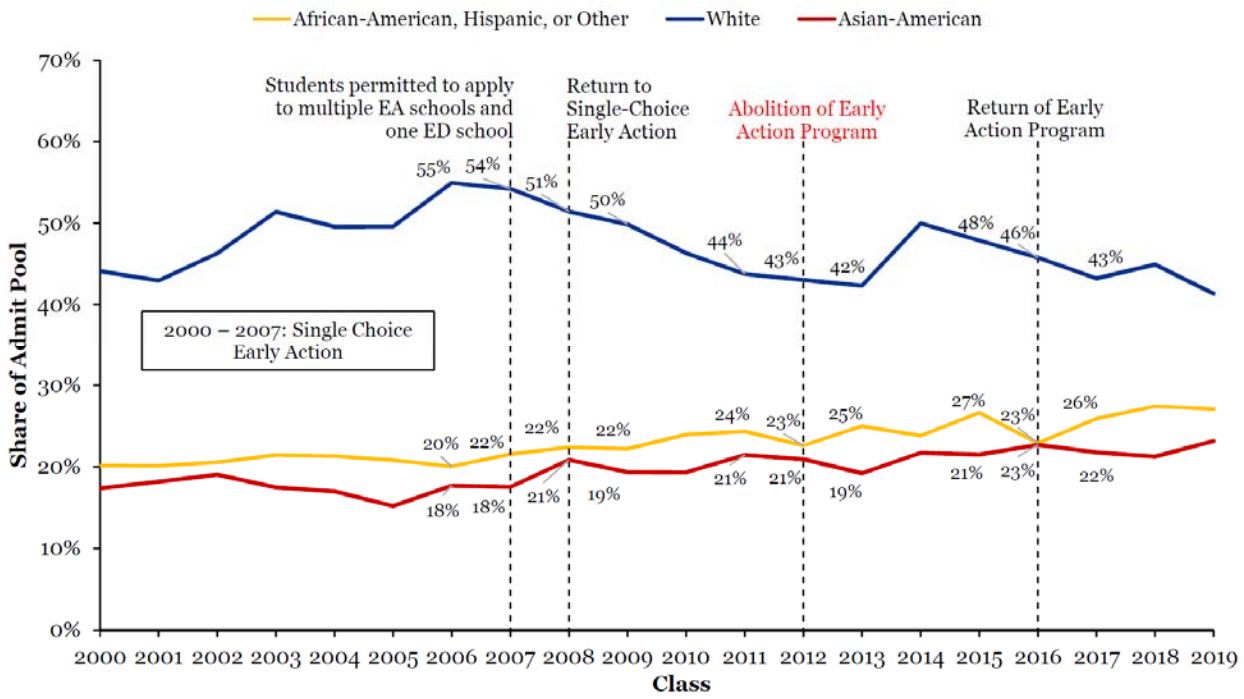
Note: Applicants classified as "Native American / Hawaiian" are grouped with applicants classified as "Other." Data for classes 2018 – 2019 are reconstructed using a methodology that replicates the produced aggregate data for classes 2000 – 2017.

290. I also look at how reinstating Early Action affected the racial composition of admitted students. Exhibit 62 shows how the racial composition of admitted students has evolved over the past 20 years. Focusing on the recent period with and without Early Action, the exhibit shows that, on average, AHO admitted students comprised 25% of the entering classes without Early Action (2012 – 2015); and after Early Action was reinstated, AHO admitted students comprised 26% of the entering classes.[216] Similarly, the fraction of admitted students who are Asian-American did not fall when Early Action was reinstated.

[216] See workpaper.

Exhibit 62

Reinstating Early Action did not decrease the share of admitted students who are Hispanic, African-American, or Other



Source: HARV00032509 – 24; HARV00031695; Augmented Arcidiacono Data

Note: Applicants classified as "Native American / Hawaiian" are grouped with applicants classified as "Other." Data for classes 2018 – 2019 are reconstructed using a methodology that replicates the produced aggregate data for classes 2000 – 2017.

291. Finally, I also examine how reinstating Early Action affected matriculation rates for admitted students of different races. The patterns in Exhibit 63 undermine SFFA's suggestion that eliminating Early Action would increase racial diversity on campus. Matriculation rates rose for admitted students of *all* races after Early Action was reinstated for the class of 2016. Asian-American matriculation rates rose from 83% in the period with no Early Action to 85% after Early Action was reinstated. Matriculation rates also rose for White admitted students and those whose race is unknown.

292. Matriculation rates for AHO admitted students averaged about 70% for classes before Early Action was abolished (2000 – 2011), but dropped to an average of 65% during the years Early Action was eliminated (2012 – 2015). Matriculation rates returned to an average of about 71% for the classes after Early Action was reinstated (2016 – 2019).

293. That trend as to the matriculation rates of AHO admitted students was, in fact, a key reason Harvard chose to reinstitute Early Action, according to documents produced in this litigation.

Based on its own statistical analysis, Harvard concluded that top AHO applicants were more likely to apply to and matriculate at universities that offered them the option to apply early, and that Harvard was losing such applicants (both in their choice of whether to apply and in their choice of whether to matriculate) when it did not offer the Early Action option.[217] Harvard thus viewed restoring Early Action as a race-neutral way to better capture top AHO talent.[218] In sum, Harvard's historical experience suggests that abolishing Early Action would not help foster a racially diverse student body.[219]

Exhibit 63

Admitted students are more likely to matriculate under Early Action

	Matriculation Rate		
	Early Action Available 2000 – 2011	**Early Action Abolished 2012 – 2015**	**Early Action Reinstated 2016 – 2019**
1. White	79%	76%	82%
2. Asian American	82%	83%	85%
3. African-American, Hispanic, or Other	70%	65%	71%
4. Unknown	80%	78%	81%

Source: HARV00032509 – 24; HARV00031695; Augmented Arcidiacono Data

Note: Applicants classified as "Native American / Hawaiian" are grouped with applicants classified as "Other." Data for classes 2018 – 2019 are reconstructed using a methodology that replicates the produced aggregate data for classes 2000 – 2017.

[217] OIR Presentation at HARV00031694, HARV00031701.

[218] Memo from President Faust and Dean Smith to Members of the Corporation, "Proposed Changes in Admissions Policy," February 2, 2011, HARV00030303 – 32 at HARV00030305 – 06, HARV00030325 – 28; OIR Presentation at HARV00031694, HARV00031701; Second Interrogatory Response, pp. 17–18.

[219] In his report, Mr. Kahlenberg uses a simulation approach in which he turns off the coefficient on the Early Action indicator, which is large and positive. The logic of Mr. Kahlenberg's approach is that if the apparent positive effect on likelihood of admission associated with applying early simply reflects unobserved privilege and resources, then removing that positive effect could help foster diversity. The problem with this approach is that the estimated positive effect may in fact reflect valuable, unobserved differences in the characteristics and quality of Early Action versus Regular Decision applicants. For example, applicants who apply early to Harvard cannot apply early elsewhere. As a result, it could be that they do more research on the institution, and therefore make a more compelling case for Harvard's being a good match for their particular academic and extracurricular interests. Applying Early Action could also be a valuable signal of commitment to attending Harvard. If that is true, then turning off the Early Action preference would discard the value Harvard places on these important differentiators. For these reasons, I do not use a simulation approach to evaluating the impact of eliminating Early Action. I examine the historical record instead.

7.4. Mr. Kahlenberg's simulated race-neutral practices, like others considered above, could achieve a comparably diverse class only by changing the class in significant ways and compromising its quality

294. In this section, I address the five combinations of race-neutral admissions practices that Mr. Kahlenberg simulates. The five simulations all focus on four types of race-neutral alternatives: (1) eliminating consideration of factors that allegedly favor White applicants (consideration of whether an applicant is a lineage applicant, recruited athlete, child of Harvard faculty or staff, Early Action applicant, or on the Dean's or Director's interest lists), (2) affording a preference to low-SES candidates, (3) admitting candidates based on location, and (4) increasing the pool of disadvantaged applicants through increases in recruiting or financial aid.

295. As I discuss below, the combinations of race-neutral practices that Mr. Kahlenberg simulates—like all those discussed above—either would not enable Harvard to achieve a comparably diverse class or would enable Harvard to achieve a comparably diverse class only at a significant cost to the quality of the class.

7.4.1. An overview of Mr. Kahlenberg's simulations

296. Mr. Kahlenberg presents the results of five simulations in his report. The simulations were actually conducted by Prof. Arcidiacono, using a version of Prof. Arcidiacono's logit model of admissions that includes the personal rating. All five simulations begin in the same way. Mr. Kahlenberg first turns off the coefficients associated with race, as well as the coefficients for being disadvantaged, having applied for financial aid, being a first-generation applicant, receiving a fee waiver, being an athletic recruit, being a lineage applicant, being a child of Harvard faculty or staff, applying Early Action, and appearing on the Dean's or Director's interest lists. He then simulates other changes to the admissions process as follows:

- Simulation 1: He gives each "disadvantaged" applicant (i.e., each applicant identified as disadvantaged by Harvard's admissions officers) a preference equivalent to half the preference that recruited athletes are estimated to receive.

- Simulation 2: In addition to Simulation 1, he simulates the effect of increased recruiting and financial aid by artificially doubling the number of disadvantaged applicants in the pool.

- Simulation 3: In addition to Simulation 1, he simulates a place-based admissions practice by using his adjusted model to rank applicants

within each College Board neighborhood cluster, then admitting an equal number of the highest-ranked students from each cluster.

- Simulation 4: He repeats Simulation 3, but allows recruited athletes to retain the admissions advantage they are estimated to receive. This is the simulation on which Mr. Kahlenberg focuses in his report.

- Simulation 5: He repeats Simulation 3, but simulates the effect of increased recruiting and financial aid by artificially doubling the number of disadvantaged applicants in the pool.

297. Mr. Kahlenberg's simulations are effectively variations on the theme of those I conducted. He and I use a similar methodology to simulate the effects of race-neutral alternatives; we simply simulate different combinations of race-neutral practices. As noted above, the key difference between Mr. Kahlenberg's approach and mine is that I simulate the effects of increased consideration of a wider set of socioeconomic attributes (including neighborhood median income and high school median income, among others) and allow the admissions advantage received by each applicant to vary with the applicant's particular socioeconomic characteristics. In contrast, Mr. Kahlenberg simulates only a single form of increased socioeconomic preference—a preference for students who are identified as "disadvantaged" by Harvard's admissions officers.

7.4.2. Mr. Kahlenberg's findings

298. Despite Mr. Kahlenberg's assertion that his proposed race-neutral alternatives could generate a racially diverse class at little cost to the quality of the student body, Mr. Kahlenberg's simulations show otherwise. While the combinations of race-neutral alternatives in Simulations 1 and 2 do dramatically increase Asian-American representation, they fail to produce a substantial proportion of AHO students (see Appendix F). Under these simulations, the proportion of African-American students would drop 30–50% below that of the current Harvard student body. In simulations 3, 4, and 5, the tested combinations of race-neutral alternatives are estimated to yield a greater proportion of Hispanic students than the current student body, but to fall 20–30% short of the current proportion of African-American students.

299. Second, Mr. Kahlenberg's preferred combination of race-neutral alternatives (simulation 4) would be expected to produce a decline of 10% or more in the proportion of admitted students with a 1 or 2 on *each* of the four profile ratings (academic, extracurricular, personal, and athletic). That is a marked decline in the excellence of the class. Indeed, all of Mr. Kahlenberg's simulated combinations of race-neutral alternatives would reduce the proportion of admitted students with top

personal and athletic ratings (1 or 2), and, as noted above, would still not generate a share of admitted students who are African-American comparable to that attained by the current race-conscious regime.

300. The admitted class would also look different in other dimensions under Mr. Kahlenberg's simulations. The fraction of admitted students who are children of Harvard and Radcliffe alumni would fall substantially, as would the number of admitted students who are children of Harvard faculty and staff. The number of athletic recruits would fall to near zero in the four simulations that turn off the preference given to athletic recruits. In addition, all of Mr. Kahlenberg's simulations generate a marked increase in biological sciences concentrators, at the expense of the humanities and social sciences.

301. Mr. Kahlenberg's simulated combinations of race-neutral alternatives would also sharply increase the fraction of admitted students with financial need. In his preferred simulation, about 309 additional applicants would apply for financial aid, as compared to the status quo. That would increase Harvard's spending by about $62 million per year (assuming equal levels of aid to all four classes on campus at a given time).[220]

302. In Appendix F, I replicate Mr. Kahlenberg's other four simulations and show how his simulated classes would differ from Harvard's current student body on a wide range of dimensions. Looking across these results, I find that Mr. Kahlenberg's proposed race-neutral alternatives do a poor job of generating racial diversity, while also coming at a cost in terms of other class characteristics I understand Harvard values.

7.5. Conclusion

303. In this section, I have examined whether any race-neutral admissions practice, or combination of race-neutral practices, could enable Harvard to achieve a comparably diverse student body without lowering the quality of the admitted class (as measured by Harvard's profile ratings and other indicia) or changing the composition of the admitted class in other ways that I understand matter to Harvard. My analyses suggest that using race-neutral policies to generate diversity comes at a cost to class quality.

304. This finding is consistent with the broader academic literature, which explains that universities attempting to achieve racial diversity without considering race will necessarily be less able to select the highest-quality applicants than if they could consider race. It is also consistent with

[220] Harvard University, "Harvard at a Glance," available at https://www.harvard.edu/about-harvard/harvard-glance, accessed November 16, 2017 ("More than 55 percent of Harvard College students receive scholarship aid, and the average grant this year is $50,000. Since 2007, Harvard's investment in financial aid has climbed by more than 75 percent, from $96.6 million to $170 million per year."). See workpapers.

the results of Mr. Kahlenberg's own simulations, which show that Harvard could achieve a comparably diverse class only at a cost to the quality of the class.

_____

David Card

December 15, 2017

8. APPENDIX A

Curriculum Vita - David Card
December 2017

Business Address: Department of Economics
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Citizenship: U.S. and Canada

Current Positions: Class of 1950 Professor of Economics
Director, Center for Labor Economics (CLE)
Director, Econometrics Laboratory (EML)
Director, Labor Studies Program, National Bureau of Economic Research

Previous Positions: Assistant Professor of Business Economics
Graduate School of Business
University of Chicago, 1982-83

Assistant Professor of Economics
Princeton University, 1983-87

Professor of Economics
Princeton University, 1987-1997

Visiting Professor of Economics
Columbia University, 1990-91

Fellow, Center for Advanced Study in
Behavioral Sciences, 1996-97

Visiting Professor of Economics
Princeton University, 2000-2001

Visiting Professor of Economics
Harvard University, 2008

Education: Queen's University (Kingston), B.A. 1978
Princeton University, Ph.D. 1983

Editorial Positions: Co-editor **American Economic Review**, 2002 - 2005.
Co-editor **Econometrica**, 1993-97
Associate Editor **Journal of Labor Economics** 1988-92

Editorial Boards:	**Journal of Population Economics**, 2001- **AEJ: Applied Economics**, 2007- **Quarterly Journal of Economics**, 2008-
Awards and Prizes:	Doctor of Laws (Honoris Causa) University of Ottawa, 2017 Doctor of Laws (Honoris Causa) University of Guelph, 2015 BBVA Foundation Frontiers of Knowledge Award, 2015 J.K. Galbraith Fellow, American Academy of Political and Social Science, 2013 Frisch Medal, 2007 (for 2005 paper in **Econometrica** with D. Hyslop) UC Berkeley Distinguished Service Award, 2007 IZA Prize in Labor Economics, 2006 Fellow, Society of Labor Economics, 2004 Doctor of Laws (Honoris Causa) Queen's University (Kingston), 1999 John Bates Clark Prize, American Economic Assoc., 1995 Fellow, American Academy of Arts and Sciences, 1998 Douglas Purvis Prize, 1994 Fellow of the Econometric Society, 1992 Manufacturers Hanover Preceptorship, Princeton Univ., 1983-88 Prince of Wales Prize, Queen's University, 1978
Invited Lectures:	Condliffe Lecture, University of Canterbury, June 2014 Arrow Lectures, Stanford University, May 2013 Lampman Lecture, University of Wisconsin Madison, May 2013 Woytinsky Lecture, University of Michigan, March 2012. Snyder Lecture, UC Santa Barbara, April 2011. Ely Lecture, American Economic Association, January 2009 Woodward Lecturer, University British Columbia, March 2008. Dennis Sargan Lecture to Royal Economic Society, 2006. Adam Smith Lecture to European Labor Economics Association, 2006. Fisher-Schultz Lecture to Econometric Society, 2002. Alfred Marshall Lecture, Cambridge University, 2000.
Advisory Boards:	National Academy of Science Committee on Nat. Statistics (2012-2015) "What Works Clearinghouse" Expert Panel Review (Chair), US Department of Education, October 2008. AEA Representative to US Census Advisory Committee, 1991-96 Statistics Canada Advisory Committee, 1990-2002 Advisory Council, ICPSR, 1994-96. Joint Center for Poverty Research, 1997-99 National Research Council Institute of Medicine Board on Children, Youth and Families, 1998-2001. RWI – Essen Advisory Board, 2005-2011. Comitato Scientifico Labor, Laboratorio R. Revelli, 2006-2009.

Selected Review Panels and Assignments:	National Institute of Health, Social Sciences, Nursing, Epidemiology, and Methods (SNEM) Review Panel, 1998-2003 Russell Sage Foundation Immigration Advisory Committee, 1999- 2001. Government of Spain Severo Ochoa Program (2014) Campbell Collaboration (2016)
Professional Societies:	Elected member of the Council, Econometric Society, 2007-2012 Elected President of Society of Labor Economics for 2010/11 President of Western Economics Association for 2015/2016 Elected Vice President of American Economic Association for 2014/2015

Books:

(co-edited with Steven Raphael). *Immigration, Poverty, and Socioeconomic Inequality*. New York: Russell Sage Foundation, 2013.

(co-authored with Alan B. Krueger; edited by Randall Akee and Klaus Zimmerman). *Wages, School Quality, and Employment Demand*. Oxford: Oxford University Press, 2011.

(co-edited with Orley Ashenfelter) *Handbook of Labor Economics* (volumes 4a-4b). Amsterdam: Elsevier, 2011.

(co-edited with Alan Auerbach and John Quigley). *Poverty, the Distribution of Income, and Public Policy*. New York: Russell Sage Foundation, 2006.

(co-edited with Richard Blundell and Richard B. Freeman) *Seeking a Premier Economy*. Chicago: University of Chicago Press for NBER, 2004.

(co-edited with Rebecca M. Blank) *Finding Work: Jobs and Welfare Reform.* New York: Russell Sage Foundation, 2000.

(co-edited with Orley Ashenfelter) *Handbook of Labor Economics* Volumes 3a-3c. Amsterdam: Elsevier, 1999.

(co-authored with Alan B. Krueger) *Myth and Measurement: The New Economics of the Minimum Wage*. Princeton: Princeton University Press, 1995. Second Edition 2016.

(co-edited with Richard B. Freeman). *Small Differences that Matter: Labor Markets and Income Maintenance in Canada and the United States*. Chicago: University of Chicago Press, 1993.

Journal Articles and Chapters in Books:

(with Stefan Bender, Nicolas Bloom, John Van Reenen, and Stephani Wolter). "Management Practices, Workforce Selection, and Productivity." Journal of Labor Economics Forthcoming 2018.

(with Jochen Kluve and Andrea Weber). "What Works? A Meta Analysis of Recent Active Labor Market Program Evaluations. " Journal of the European Economic Association October 2017.

(with Zhuan Pei, David S. Lee and Andrea Weber). "Regression Kink Design: Theory and Practice." Advances in Econometrics Forthcoming 2017.

(with Ana Rute Cardoso, Joerg Heining, and Patrick Kline). "Firms and Labor Market Inequality: Evidence and Some Theory." Journal of Labor Economics Forthcoming 2018.

(with Laura Giuliano). "Can Universal Screening Increase the Representation of Low Income and Minority Students in Gifted Education?" Proceedings of the National Academy of Science 113, November 2016.

(with Laura Giuliano). "Can Tracking Raise the Test Scores of High-Ability Minority Students?" American Economic Review October 2016.

(with Ana Rute Cardoso and Patrick Kline). "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women." Quarterly Journal of Economics May 2016.

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9. APPENDIX B

9.1. Documents relied upon

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10. APPENDIX C

10.1. Parent occupations

Exhibit 64

Mother's occupation differs by race

	Occupation Category	White	Asian-American	African-American	Hispanic or Other	Race Missing
1.	Homemaker	16.8%	18.5%	7.1%	15.9%	17.1%
2.	Other	15.8%	14.9%	24.2%	22.3%	17.3%
3.	Pre-K through Grade 12 Educational Instruction & Library	10.0%	4.3%	8.0%	9.6%	7.0%
4.	Health Diagnosing and Treating Practitioners	8.0%	8.0%	6.6%	4.3%	8.0%
5.	Business Executive (management, administrator)	7.4%	5.1%	6.7%	5.6%	6.5%
6.	Lawyers, Judges and Related Workers	4.3%	0.7%	2.6%	2.2%	3.4%
7.	Other Healthcare Occupations Incl. Nurses	4.2%	3.7%	9.6%	3.2%	3.6%
8.	Unemployed	4.0%	6.3%	8.3%	7.6%	5.2%
9.	Office and Administrative Support	3.7%	2.7%	4.2%	4.4%	2.5%
10.	Self-Employed	3.4%	3.9%	2.2%	3.2%	3.7%
11.	Business and Financial Operations	3.3%	4.8%	3.6%	2.7%	3.5%
12.	Art, Design and Media	3.0%	1.0%	0.9%	1.4%	2.6%
13.	Postsecondary Teachers	2.4%	2.1%	1.2%	1.3%	2.4%
14.	Sales and Related	2.4%	1.8%	1.9%	2.3%	1.7%
15.	Life, Physical and Social Sciences	2.0%	4.9%	0.7%	1.0%	3.4%
16.	Architecture and Engineering	1.8%	4.9%	0.8%	1.5%	3.8%
17.	Counselors, Social Workers, Community Service	1.8%	0.7%	3.3%	1.9%	1.4%
18.	Other Management (Excl. Business Execs)	1.7%	1.1%	1.7%	1.5%	1.0%
19.	Computer and Mathematical	1.4%	6.1%	1.1%	0.8%	3.8%
20.	Skilled Trades Incl. Construction and Extraction	1.2%	3.3%	2.9%	5.3%	1.3%
21.	Low Skill.	0.6%	0.9%	1.4%	1.6%	0.3%
22.	Entertainers, Performers and Sports Related Workers	0.5%	0.4%	0.2%	0.2%	0.4%
23.	Protective Service	0.1%	0.0%	0.6%	0.3%	0.1%
24.	Military	0.1%	0.0%	0.4%	0.1%	0.0%

Source: Augmented Arcidiacono Data

Note: Sample consists of Prof. Arcidiacono's expanded sample for the classes of 2014 – 2019. For the class of 2018, the "Unemployed" category is combined with the "Homemaker" category in my year-by-year models, affecting 10 observations.

Exhibit 65

Father's occupation differs by race

	Occupation Category	White	Asian-American	African-American	Hispanic or Other	Race Missing
1.	Business Executive (management, administrator)	17.2%	11.8%	7.8%	11.4%	14.5%
2.	Other	13.9%	13.4%	31.0%	24.1%	15.5%
3.	Health Diagnosing and Treating Practitioners	9.7%	9.6%	6.6%	6.1%	10.4%
4.	Architecture and Engineering	9.1%	17.7%	5.8%	6.8%	13.8%
5.	Self-Employed	8.2%	7.5%	4.6%	6.8%	7.7%
6.	Lawyers, Judges and Related Workers	7.7%	1.3%	2.6%	3.9%	5.4%
7.	Skilled Trades Incl. Construction and Extraction	4.8%	4.2%	7.4%	13.6%	3.3%
8.	Computer and Mathematical	4.0%	8.8%	2.7%	2.3%	6.8%
9.	Sales and Related	3.8%	1.8%	2.6%	3.5%	2.5%
10.	Postsecondary Teachers	3.1%	4.9%	1.9%	1.4%	4.1%
11.	Business and Financial Operations	3.0%	2.3%	2.7%	2.2%	2.1%
12.	Life, Physical and Social Sciences	2.6%	6.6%	1.0%	1.2%	4.4%
13.	Pre-K through Grade 12 Educational Instruction & Library	2.4%	0.7%	2.4%	2.0%	1.3%
14.	Other Management (Excl. Business Execs)	2.2%	1.3%	1.3%	1.8%	1.2%
15.	Unemployed	2.2%	3.2%	8.0%	4.8%	2.7%
16.	Art, Design and Media	1.4%	0.5%	0.7%	0.8%	1.0%
17.	Protective Service	0.9%	0.2%	1.9%	1.8%	0.5%
18.	Counselors, Social Workers, Community Service	0.9%	1.0%	2.4%	0.7%	0.8%
19.	Military	0.9%	0.3%	1.6%	0.9%	0.3%
20.	Low Skill.	0.6%	0.8%	1.4%	1.8%	0.2%
21.	Office and Administrative Support	0.6%	0.8%	1.2%	1.0%	0.5%
22.	Entertainers, Performers and Sports Related Workers	0.4%	0.2%	0.5%	0.4%	0.4%
23.	Other Healthcare Occupations Incl. Nurses	0.4%	0.7%	1.5%	0.5%	0.4%
24.	Homemaker	0.3%	0.2%	0.2%	0.3%	0.3%

Source: Augmented Arcidiacono Data

Note: Sample consists of Prof. Arcidiacono's expanded sample for the classes of 2014 – 2019. For the class of 2018, the "Unemployed" category is combined with the "Homemaker" category in my year-by-year models, affecting 5 observations.

11. APPENDIX D

11.1. Primary activities

Exhibit 66

Primary activities differ by race

Primary Activity	White	Asian-American	African-American	Hispanic or Other	Race Missing
1. **Varsity athletics**	26%	16%	26%	24%	16%
2. **Community service**	22%	27%	25%	27%	26%
3. **Other**	14%	14%	14%	14%	15%
4. **JV athletics**	13%	7%	12%	11%	11%
5. **Instrumental music**	12%	17%	9%	10%	15%
6. **Academic**	11%	11%	13%	13%	10%
7. **Politics**	10%	9%	11%	10%	9%
8. **Work**	9%	7%	8%	8%	8%
9. **Science or math**	8%	18%	5%	7%	14%
10. **Speech and debate**	7%	9%	6%	6%	8%
11. **Club athletics**	6%	4%	5%	6%	5%
12. **Drama**	6%	2%	4%	4%	4%
13. **Journalism**	5%	6%	3%	4%	6%
14. **Career**	5%	8%	5%	5%	8%
15. **Religious**	3%	3%	5%	4%	2%
16. **Vocal music**	3%	2%	3%	3%	2%
17. **Dance**	3%	3%	4%	3%	3%
18. **Computer**	2%	4%	2%	2%	4%
19. **Foreign language**	2%	2%	2%	2%	2%
20. **Art**	2%	2%	2%	2%	3%
21. **Missing**	2%	1%	6%	4%	1%
22. **Environmental**	1%	2%	1%	1%	1%
23. **Foreign exchange**	1%	1%	1%	1%	1%
24. **Cultural**	1%	2%	3%	2%	1%
25. **Robotics**	1%	1%	1%	1%	1%
26. **Family**	1%	1%	1%	1%	1%
27. **LGBT**	1%	0%	0%	1%	0%
28. **School spirit**	0%	0%	1%	1%	0%
29. **Junior ROTC**	0%	0%	1%	1%	0%

Sorce: Augmented Arcidiacono Data

Note: Data are from applicants to the classes of 2017 – 2019 in Professor Arcidiacono's expanded sample. Primary activities consist of activities that applicants listed as either activity 1 or activity 2. Categories for activities can vary year to year.

12. APPENDIX E

12.1. Variables used in logit model of admissions

Variable Name	Variable Description	Arcidiacono Variable	Card Model	
			Pooled	Year-by-year
Race Variables				
race	Mutually exclusive race categories, based on ethnic_group_cde field with categories: "White," "Black," "Hispanic, Mexican, or Puerto Rican," "Asian," "Native American," "Hawaiian or Pacific Islander," "Race Missing."	✓	✓	
racecoll	Mutually exclusive race categories, based on ethnic_group_cde field with categories: "White," "Black," "Hispanic and Other," "Asian," "Race Missing." "Other" includes Mexican, Puerto Rican, Native American, Hawaiian, and Pacific Islander.			✓
Base Controls				
year	Harvard class to which applicant applies: 2014 to 2019	✓	✓	✓
female	Indicator for whether applicant indicated "Female" in a sex code entry field	✓	✓	✓
disadvantaged	Indicator for whether applicant was flagged by admissions staff, based on application, as likely socioeconomically disadvantaged or HFAI eligible	✓	✓	✓
fgcl	Indicator for first generation college applicant	✓	✓	✓
earlyDecision	Indicator for Early Action applicant	✓	✓	✓
athlete	Indicator for athletic profile rating of 1	✓	✓	✓
legacy	Indicator for whether at least one of applicant's parents attended Harvard	✓	✓	✓
double_legacy	Indicator for whether both of applicant's parents attended Harvard	✓	✓	✓
faculty_or_staff_kid	Indicator for whether applicant is child of Harvard faculty or staff	✓	✓	✓
deanDirectorPref	Indicator for whether applicant is on Dean's or Director's Interest Lists	✓	✓	✓
waiver_tot	Indicator for whether applicant requested a fee waiver	✓	✓	✓
finaid	Indicator for whether applicant applied for financial aid	✓	✓	✓
meduc	Categories for mother's level of education: "Less than college," "College graduate," "Master's," "MD/JD/PhD," "Missing"	✓	✓	✓
feduc	Categories for father's level of education: "Less than college," "College graduate," "Master's," "MD/JD/PhD," "Missing"	✓	✓	✓
intendedMajor	Categories for applicant's intended major: "Social sciences," "Humanities," "Biological sciences," "Physical sciences," "Engineering," "Mathematics," "Computer Sciences," "Unspecified"	✓	✓	✓
docketFE	Docket to which applicant's high school is assigned	✓	✓	✓

Variable Name	Variable Description	Arcidiacono Variable	Card Model	
			Pooled	Year-by-year
Academic Variables				
SACTmath_std	Normalized ACT/SAT math score	✓	✓	✓
SACTverb_std	Normalized ACT/SAT verbal score	✓	✓	✓
SAT2avg_std	Normalized average SAT II subject test score	✓	✓	✓
gpa_converted_std	Normalized converted GPA	✓	✓	✓
academic_index_std	Normalized academic index	✓	✓	✓
academic_index2p	Normalized academic index quadratic multiplied by indicator for positive normalized academic index	✓	✓	✓
academic_index2m	Normalized academic index quadratic multiplied by indicator for negative normalized academic index	✓	✓	✓
flaggpa	Indicator for converted GPA equal to 35	✓	✓	✓
m_SAT2avg	Indicator for missing average SAT II score	✓	✓	✓
Ratings Variables				
APEA_combos	Combinations of athletic, personal, extracurricular, and academic ratings. Each profile rating has categories: 1, 2, 3, 4, 5, or 6. Exact combinations are determined at the applicant level (e.g. any applicant who received four ratings of 3 would have the exact combination 3333). Combinations that appear in the sample at least 100 times have their own control group. The remainder of combinations are combined with the control group with the closest admission rate.		✓	✓
teach_combos	Combinations of school support ratings, assigned by Admissions Committee, based on two teacher recommendations. Each teacher rating has categories: 1, 2, 3, 4, 5, and Missing. Combinations are determined at the applicant level (e.g. any applicant who received ratings of 1 and 2 would have the combination 12). Combinations that appear in the sample at least 100 times have their own control group. The remainder of combinations are combined with the control group with the closest admission rate.		✓	✓
counslor_rat_abbr	School support rating, assigned by Admissions Committee, based on applicant's recommendation from guidance counselor. Categories: 1, 2, 3, 4, 5, and Missing.	✓	✓	✓
alum_combos	Combinations of alumni interview overall and personal ratings. Each alumni interview rating has categories: 1, 2, 3, 4, 5 or 6, and Missing. Combinations are determined at the applicant level (e.g. any applicant who received an overall rating of 1 and a personal rating of 2 would have the combination 12). Combinations that appear in the sample at least 100 times have their own control group. The remainder of combinations are combined with the control group with the closest admission rate.		✓	✓

			Card Model	
Variable Name	**Variable Description**	**Arcidiacono Variable**	**Pooled**	**Year-by-year**
Contextual Factors				
father_occ_cat	Mother's occupation category; see Appendix C.		✓	✓
mother_occ_cat	Father's occupation category; see Appendix C.		✓	✓
father_deceased_yn	Indicator for whether father is marked as deceased; defaulted to false for missing entries		✓	✓
mother_deceased_yn	Indicator for whether mother is marked as deceased; defaulted to false for missing entries		✓	✓
parent_ivy	Indicator for whether at least one parent attended an Ivy League school (not counting Ivy sister schools); defaulted to false for missing entries		✓	✓
rural	Indicator for whether applicant's high school county is not in a Metropolitan or Micropolitan Statistical Area; for applicants missing high school city field, permanent address city is used.		✓	✓
intendedCareer	Intended career indicated by applicant, from a choice of 15 career categories, "Other," "Undecided," or "Unknown"		✓	✓
school_type	School type (public, private, Catholic, or missing)		✓	✓
legacy_grad	Indicator for whether at least one of applicant's parents went to Harvard Graduate School		✓	✓
perm_res	Indicator for whether applicant is a United States permanent resident		✓	✓
staffOP	Combination of staff interview overall and personal ratings. Control groups defined: (1) ratings combinations of 1 and 2, (2) combinations of 2 and 3, (3) both ratings of 3, and (4) remainder.		✓	
total_work	Total hours of work reported in activity description			✓
primcoll*	Indicators for applicant's primary extracurricular activities (collapsed into the following groups: (1) Varsity, JV, or Club athletics; (2) Computer, Speech and Debate, Journalism, Science, Math, Robotics, or Academic; (3) Volunteer or Religious; (4) Environmental, Family, LGBT, School spirit, or Other; (5) Dance, Drama, or Vocal music; (6) Instrumental music; (7) Politics; (8) Work; (9) Career; (10) Cultural, Foreign exchange, or Foreign language; (11) Missing; and (12) Junior ROTC). A primary activity is defined as an activity the applicant lists in the first or second activity field of her application.			✓
staff_yn	Indicator for whether applicant received a staff interview rating			✓
born_USA	Indicator for whether applicant was born outside of United States			✓
outside_US_yn	Indicator for whether applicant lived outside of United States			✓

Variable Name	Variable Description	Arcidiacono Variable	Card Model	
			Pooled	Year-by-year
High School Characteristics				
The College Board aggregates applicant-level data to the high school level, based on student's AICODE. All high school variables are interacted with the SAT state indicator unless denoted with †.				
sat_state	Indicator for whether applicant's state has more SAT takers than ACT takers that applied to Harvard (a student is marked as an SAT/ACT taker if the corresponding composite score is available for that student)		✓	✓
hs_sat_math	Average score on the math section of the SAT I for all students at applicant's high school		✓	✓
hs_sat_cr	Average score on the verbal section of the SAT for all students at applicant's high school		✓	✓
hs_sat_w	Average score on the writing section of the SAT for all students at applicant's high school		✓	✓
hs_english	Percent of students at applicant's high school who report that they speak only English		✓	✓
hs_app_outofstate	Percent of students at applicant's high school who applied to an out of state college		✓	✓
hs_avg_num_ap	Average # of AP tests taken by students at applicant's high school		✓	✓
hs_fin_aid	Percent of students at applicant's high school who require financial aid for college		✓	✓
hs_avg_hon	Average # of honors courses taken by students at applicant's high school		✓	✓
hs_parent_ed	Percent of students at applicant's high school who reported that no parent had education beyond high school		✓	✓
hs_avg_sat_sends	Average number of scores sends for students at applicant's high school		✓	✓
hs_coll_admit_rate	Average rate of admission for colleges receiving score sends from students at applicant's high school		✓	✓
hs_black†	ACS-based percent of students at applicant's high school who are Black		✓	✓
hs_white†	ACS-based percent of students at applicant's high school who are White		✓	✓
hs_hispanic†	ACS-based percent of students at applicant's high school who are Hispanic		✓	✓
hs_med_income†	ACS-based median family income of students at applicant's high school		✓	✓
hs_pov_line†	ACS-based percent of students at applicant's high school who are below the poverty line		✓	✓
hs_house_val†	ACS-based median value of home for students at applicant's high school, as a percentage of average state value		✓	✓

Variable Name	Variable Description	Arcidiacono Variable	Card Model	
			Pooled	Year-by-year
Neighborhood Characteristics				
The College Board aggregates applicant-level data to the educational neighborhood (one or more contiguous census tracts). All neighborhood variables are interacted with the SAT state indicator unless denoted with †.				
n_sat_math	Average score on the math section of the SAT for all students in applicant's neighborhood		✓	✓
n_sat_cr	Average score on the verbal section of the SAT for all students in applicant's neighborhood		✓	✓
n_sat_w	Average score on the writing section of the SAT for all students in applicant's neighborhood		✓	✓
n_english	Percent of students in applicant's neighborhood who report that they only speak English		✓	✓
n_app_outofstate	Percent of students in applicant's neighborhood who applied to an out of state college		✓	✓
n_avg_num_ap	Average # of AP tests taken by students in applicant's neighborhood		✓	✓
n_fin_aid	Percent of students in applicant's neighborhood who require financial aid for college		✓	✓
n_avg_hon	Average # of honors courses taken by students in applicant's neighborhood		✓	✓
n_parent_ed	Percent of students in applicant's neighborhood who reported that no parent had education beyond high school		✓	✓
n_avg_sat_sends	Average number of score sends for students in applicant's neighborhood		✓	✓
n_coll_admit_rate	Average rate of admissions for colleges receiving score sends from students in applicant's neighborhood		✓	✓
n_black†	ACS-based percent of students in applicant's neighborhood who are Black		✓	✓
n_white†	ACS-based percent of students in applicant's neighborhood who are White		✓	✓
n_hispanic†	ACS-based percent of students in applicant's neighborhood who are Hispanic		✓	✓
n_med_income_imp†	ACS-based median family income of students in applicant's neighborhood, missing values filled with mean		✓	✓
n_pov_line_imp†	ACS-based percent of students in applicant's neighborhood who are below the poverty line, missing values filled with mean		✓	✓
n_house_val_imp†	ACS-based median value of home for students in applicant's neighborhood, as a percentage of average state value, missing values filled with mean		✓	✓

			Card Model	
Variable Name	**Variable Description**	**Arcidiacono Variable**	**Pooled**	**Year-by-year**
m_n_pov_line†	Indicator for missing neighborhood poverty line variable		✓	✓
m_n_med_income†	Indicator for missing neighborhood median income variable		✓	✓
m_n_house_val†	Indicator for missing neighborhood house value variable		✓	✓

Note: I assign parents to be mothers or fathers using the father/mother_type variables for years before 2017, and the parent1/2_type variables from 2017 and on due to data availability. I assign parents to be "mother figures" (e.g., "mother", "aunt") or "father figures" (e.g., "father", "grandfather") using the variables father/mother_type for years before 2017, and using parent1/2_type from 2017 and on due to data availability. When the parental type variable is gender neutral (e.g., "guardian"), I use gender information from the parent1/2_gender variable in my assignment.

13. APPENDIX F

13.1. Mr. Kahlenberg's Simulations

Exhibit 67

Mr. Kahlenberg's Simulation 1: Impact on class quality and composition

	Outcome Measures	Model Baseline: Status Quo [3]	Simulated Class: Removing Consideration of Race, Preferences, Athletes; Preference Disadvantaged Students [2] Predicted Value	% Change
	Race			
1.	White	40.4%	38.3%	-5%
2.	Asian-American	23.7%	34.0%	+43%
3.	Hispanic	12.9%	11.4%	-12%
4.	African-American	13.6%	6.6%	-51%
5.	Other	9.3%	9.7%	+4%
	Academic			
6.	Average Composite SAT Score	2239	2235	-0.2%
7.	Average Composite ACT Score	33.3	33.4	+0.3%
8.	Average Converted GPA	77.0	77.3	+0.5%
9.	Average Academic Index	228.2	228.7	+0.3%
	Fraction with Profile Rating of 1 or 2			
10.	Academic	76%	78%	+2%
11.	Extracurricular	61%	63%	+4%
12.	Personal	73%	69%	-5%
13.	Athletic	27%	15%	-44%
	Average Profile Rating (higher is worse)			
14.	Academic	2.22	2.19	-1%
15.	Extracurricular	2.40	2.38	-0.4%
16.	Personal	2.27	2.31	+2%
17.	Athletic	3.04	3.41	+12%
	Applicant Characteristics			
18.	Number of Lineage Students	293	89	-70%
19.	Number of Double Lineage Students	78	20	-74%
20.	Number of Recruited Athletes	186	14	-93%
21.	Number of Children of Harvard Faculty or Staff	50	36	-28%
22.	Number of Students on Dean's and Director's Interest Lists	Redacted		
23.	Number of Female	859	844	-2%

Socioeconomic Status			
24. Number First Generation College	120	236	+97%
25. Number Disadvantaged	305	808	+165%
26. Number Fee Waiver	303	623	+106%
27. Number Financial Aid	1141	1354	+19%
Concentrations			
28. Social Sciences	25%	24%	-6%
29. Humanities	14%	12%	-10%
30. Biological Sciences	21%	23%	+9%
31. Physical Science	6.9%	7.8%	+12%
32. Engineering	13%	15%	+10%
33. Computer Science	6.1%	6.5%	+6%
34. Mathematics	6.5%	6.6%	+1%
35. Unspecified	6.7%	5.1%	-23%

Source: Arcidiacono Data

Note:
[1] Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's expanded sample. Prof. Arcidiacono's Model 6 is used with interactions between race and year, disadvantaged and year, and with the exclusion of the overall rating.
[2] Mr. Kahlenberg removes consideration of an applicant's race and lineage status, whether the applicant applied Early Action, whether the applicant's parents are Harvard faculty or staff, whether the applicant appeared on the Dean's or Director's interest list, whether the applicant was identified as disadvantaged, whether the applicant applied for a waiver of the application fee, whether the applicant is a first-generation college student, whether the applicant applied for financial aid, and whether the applicant is a recruited athlete. In addition, recruited athletes are assigned extracurricular and athletic ratings of 2. Mr. Kahlenberg gives a boost to disadvantaged applicants by adding to their admission index a value equal to half the value of the "athlete" coefficient in the model.
[3] This analysis reports values entirely from the predicted class. In his report, Mr. Kahlenberg reports average academic index, extracurricular rating, and personal rating values from the actul admitted class, while reporting the racial composition and share of disadvantaged students from the predicted class, under the "Status Quo" specification.

Exhibit 68

Mr. Kahlenberg's Simulation 2: Impact on class quality and composition

	Outcome Measures	Model Baseline: Status Quo [3]	Simulated Class: Removing Consideration of Race, Preferences, Athletes; Preference Disadvantaged Students; Double Number of Disadvantaged Applicants [2] Predicted Value	% Change
	Race			
1.	White	40.4%	34.6%	-14%
2.	Asian-American	23.7%	34.5%	+45%
3.	Hispanic	12.9%	13.7%	+6%
4.	African-American	13.6%	8.0%	-41%
5.	Other	9.3%	9.1%	-1%
	Academic			
6.	Average Composite SAT Score	2239	2214	-1%
7.	Average Composite ACT Score	33.3	33.2	-0.3%
8.	Average Converted GPA	77.0	77.2	+0.4%
9.	Average Academic Index	228.2	227.6	-0.2%
	Fraction with Profile Rating of 1 or 2			
10.	Academic	76%	74%	-3%
11.	Extracurricular	61%	63%	+3%
12.	Personal	73%	71%	-2%
13.	Athletic	27%	14%	-50%
	Average Profile Rating (higher is worse)			
14.	Academic	2.22	2.24	+1%
15.	Extracurricular	2.40	2.40	+0.4%
16.	Personal	2.27	2.29	+1%
17.	Athletic	3.04	3.51	+15%
	Applicant Characteristics			
18.	Number of Lineage Students	293	61	-79%
19.	Number of Double Lineage Students	78	14	-82%
20.	Number of Recruited Athletes	186	11	-94%
21.	Number of Children of Harvard Faculty or Staff	50	28	-44%
22.	Number of Students on Dean's and Director's Interest Lists	**Redacted**		
23.	Number of Female	859	842	-2%

Socioeconomic Status			
24. Number First Generation College	120	328	+173%
25. Number Disadvantaged	305	1197	+292%
26. Number Fee Waiver	303	885	+192%
27. Number Financial Aid	1141	1503	+32%
Concentrations			
28. Social Sciences	25%	24%	-5%
29. Humanities	14%	12%	-13%
30. Biological Sciences	21%	24%	+13%
31. Physical Science	6.9%	8.1%	+16%
32. Engineering	13%	15%	+11%
33. Computer Science	6.1%	6.1%	-0.1%
34. Mathematics	6.5%	6.2%	-5%
35. Unspecified	6.7%	4.9%	-26%

Source: Arcidiacono Data

Note:
[1] Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's expanded sample. Prof. Arcidiacono's Model 6 is used with interactions between race and year, disadvantaged and year, and with the exclusion of the overall rating.
[2] Mr. Kahlenberg doubles the number of disadvantaged applicants. Mr. Kahlenberg removes consideration of an applicant's race and lineage status, whether the applicant applied Early Action, whether the applicant's parents are Harvard faculty or staff, whether the applicant appeared on the Dean's or Director's interest list, whether the applicant was identified as disadvantaged, whether the applicant applied for a waiver of the application fee, whether the applicant is a first-generation college student, whether the applicant applied for financial aid, and whether the applicant is a recruited athlete. In addition, recruited athletes are assigned extracurricular and athletic ratings of 2. Mr. Kahlenberg gives a boost to disadvantaged applicants by adding to their admission index a value equal to half the value of the "athlete" coefficient in the model.
[3] This analysis reports values entirely from the predicted class. In his report, Mr. Kahlenberg reports average academic index, extracurricular rating, and personal rating values from the actul admitted class, while reporting the racial composition and share of disadvantaged students from the predicted class, under the "Status Quo" specification.

Exhibit 69

Mr. Kahlenberg's Simulation 3: Impact on class quality and composition

	Outcome Measures	Model Baseline: Status Quo [3]	Simulated Class Using Cluster-Based Admission: Removing Consideration of Race, Preferences, Athletes; Preference Disadvantaged Students [2] Predicted Value	% Change
	Race			
1.	White	40.4%	37.9%	-6%
2.	Asian-American	23.7%	29.5%	+24%
3.	Hispanic	12.9%	13.7%	+6%
4.	African-American	13.6%	9.6%	-29%
5.	Other	9.3%	9.3%	+0.4%
	Academic			
6.	Average Composite SAT Score	2239	2206	-1%
7.	Average Composite ACT Score	33.3	33.1	-1%
8.	Average Converted GPA	77.0	77.2	+0.3%
9.	Average Academic Index	228.2	227.0	-1%
	Fraction with Profile Rating of 1 or 2			
10.	Academic	76%	70%	-8%
11.	Extracurricular	61%	58%	-5%
12.	Personal	73%	66%	-9%
13.	Athletic	27%	14%	-49%
	Average Profile Rating (higher is worse)			
14.	Academic	2.22	2.28	+2%
15.	Extracurricular	2.40	2.45	+2%
16.	Personal	2.27	2.34	+3%
17.	Athletic	3.04	3.50	+15%
	Applicant Characteristics			
18.	Number of Lineage Students	293	66	-77%
19.	Number of Double Lineage Students	78	16	-80%
20.	Number of Recruited Athletes	186	9	-95%
21.	Number of Children of Harvard Faculty or Staff	50	28	-43%
22.	Number of Students on Dean's and Director's Interest Lists	**Redacted**		
23.	Number of Female	859	844	-2%

Socioeconomic Status			
24. Number First Generation College	120	294	+145%
25. Number Disadvantaged	305	996	+227%
26. Number Fee Waiver	303	784	+159%
27. Number Financial Aid	1141	1465	+28%
Concentrations			
28. Social Sciences	25%	23%	-9%
29. Humanities	14%	12%	-16%
30. Biological Sciences	21%	23%	+6%
31. Physical Science	6.9%	8.2%	+18%
32. Engineering	13%	15%	+14%
33. Computer Science	6.1%	6.5%	+6%
34. Mathematics	6.5%	7.4%	+13%
35. Unspecified	6.7%	5.4%	-19%

Source: Arcidiacono Data

Note:
[1] Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's expanded sample. Prof. Arcidiacono's Model 6 is used with interactions between race and year, disadvantaged and year, and with the exclusion of the overall rating.
[2] Applicants are ranked in descending order of admission index and an equal number of applicants are admitted from each neighborhood cluster. Mr. Kahlenberg removes consideration of an applicant's race and lineage status, whether the applicant applied Early Action, whether the applicant's parents are Harvard faculty or staff, whether the applicant appeared on the Dean's or Director's interest list, whether the applicant was identified as disadvantaged, whether the applicant applied for a waiver of the application fee, whether the applicant is a first-generation college student, whether the applicant applied for financial aid, and whether the applicant is a recruited athlete. In addition, recruited athletes are assigned extracurricular and athletic ratings of 2. Mr. Kahlenberg gives a boost to disadvantaged applicants by adding to their admission index a value equal to half the value of the "athlete" coefficient in the model.
[3] This analysis reports values entirely from the predicted class. In his report, Mr. Kahlenberg reports average academic index, extracurricular rating, and personal rating values from the actul admitted class, while reporting the racial composition and share of disadvantaged students from the predicted class, under the "Status Quo" specification.

Exhibit 70

Mr. Kahlenberg's Simulation 4: Impact on class quality and composition

	Outcome Measures	Model Baseline: Status Quo [3]	Simulated Class Using Cluster-Based Admission: Removing Consideration of Race, Preferences; Preference Disadvantaged Students [2] Predicted Value	% Change
	Race			
1.	White	40.4%	39.6%	-2%
2.	Asian-American	23.7%	27.6%	+16%
3.	Hispanic	12.9%	13.5%	+4%
4.	African-American	13.6%	10.1%	-26%
5.	Other	9.3%	9.2%	-1%
	Academic			
6.	Average Composite SAT Score	2239	2191	-2%
7.	Average Composite ACT Score	33.3	32.9	-1%
8.	Average Converted GPA	77.0	77.1	+0.2%
9.	Average Academic Index	228.2	225.9	-1%
	Fraction with Profile Rating of 1 or 2			
10.	Academic	76%	66%	-13%
11.	Extracurricular	61%	54%	-13%
12.	Personal	73%	65%	-10%
13.	Athletic	27%	20%	-25%
	Average Profile Rating (higher is worse)			
14.	Academic	2.22	2.33	+5%
15.	Extracurricular	2.40	2.50	+4%
16.	Personal	2.27	2.34	+3%
17.	Athletic	3.04	3.31	+9%
	Applicant Characteristics			
18.	Number of Lineage Students	293	57	-81%
19.	Number of Double Lineage Students	78	12	-85%
20.	Number of Recruited Athletes	186	150	-20%
21.	Number of Children of Harvard Faculty or Staff	50	19	-62%
22.	Number of Students on Dean's and Director's Interest Lists	Redacted		
23.	Number of Female	859	827	-4%

Socioeconomic Status			
24. Number First Generation College	120	289	+141%
25. Number Disadvantaged	305	949	+211%
26. Number Fee Waiver	303	753	+149%
27. Number Financial Aid	1141	1450	+27%
Concentrations			
28. Social Sciences	25%	23%	-7%
29. Humanities	14%	11%	-19%
30. Biological Sciences	21%	23%	+8%
31. Physical Science	6.9%	7.7%	+11%
32. Engineering	13%	15%	+11%
33. Computer Science	6.1%	6.1%	-0.2%
34. Mathematics	6.5%	7.5%	+15%
35. Unspecified	6.7%	6.2%	-7%

Source: Arcidiacono Data

Note:
[1] Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's expanded sample. Prof. Arcidiacono's Model 6 is used with interactions between race and year, disadvantaged and year, and with the exclusion of the overall rating.
[2] Applicants are ranked in descending order of admission index and an equal number of applicants are admitted from each neighborhood cluster. Mr. Kahlenberg removes consideration of an applicant's race and lineage status, whether the applicant applied Early Action, whether the applicant's parents are Harvard faculty or staff, whether the applicant appeared on the Dean's or Director's interest list, whether the applicant was identified as disadvantaged, whether the applicant applied for a waiver of the application fee, whether the applicant is a first-generation college student, and whether the applicant applied for financial aid. Mr. Kahlenberg gives a boost to disadvantaged applicants by adding to their admission index a value equal to half the value of the "athlete" coefficient in the model.
[3] This analysis reports values entirely from the predicted class. In his report, Mr. Kahlenberg reports average academic index, extracurricular rating, and personal rating values from the actul admitted class, while reporting the racial composition and share of disadvantaged students from the predicted class, under the "Status Quo" specification.

Exhibit 71

Mr. Kahlenberg's Simulation 5: Impact on class quality and composition

	Outcome Measures	Model Baseline: Status Quo [3]	Simulated Class Using Cluster-Based Admission: Removing Consideration of Race, Preferences, Athletes; Preference Disadvantaged Students; Double Number of Disadvantaged Applicants [2] Predicted Value	% Change
	Race			
1.	White	40.4%	36.1%	-11%
2.	Asian-American	23.7%	30.0%	+26%
3.	Hispanic	12.9%	14.6%	+13%
4.	African-American	13.6%	10.6%	-22%
5.	Other	9.3%	8.8%	-5%
	Academic			
6.	Average Composite SAT Score	2239	2205	-2%
7.	Average Composite ACT Score	33.3	33.1	-1%
8.	Average Converted GPA	77.0	77.1	+0.2%
9.	Average Academic Index	228.2	226.8	-1%
	Fraction with Profile Rating of 1 or 2			
10.	Academic	76%	70%	-8%
11.	Extracurricular	61%	60%	-2%
12.	Personal	73%	70%	-3%
13.	Athletic	27%	13%	-52%
	Average Profile Rating (higher is worse)			
14.	Academic	2.22	2.28	+2%
15.	Extracurricular	2.40	2.44	+2%
16.	Personal	2.27	2.30	+1%
17.	Athletic	3.04	3.54	+16%
	Applicant Characteristics			
18.	Number of Lineage Students	293	48	-84%
19.	Number of Double Lineage Students	78	13	-83%
20.	Number of Recruited Athletes	186	11	-94%
21.	Number of Children of Harvard Faculty or Staff	50	23	-54%
22.	Number of Students on Dean's and Director's Interest Lists	**Redacted**		
23.	Number of Female	859	814	-5%

Socioeconomic Status			
24. Number First Generation College	120	349	+191%
25. Number Disadvantaged	305	1298	+326%
26. Number Fee Waiver	303	971	+221%
27. Number Financial Aid	1141	1561	+37%
Concentrations			
28. Social Sciences	25%	24%	-3%
29. Humanities	14%	12%	-15%
30. Biological Sciences	21%	23%	+9%
31. Physical Science	6.9%	8.4%	+21%
32. Engineering	13%	15%	+15%
33. Computer Science	6.1%	5.3%	-12%
34. Mathematics	6.5%	6.7%	+4%
35. Unspecified	6.7%	4.9%	-27%

Source: Arcidiacono Data

Note:
[1] Sample consists of applicants to the class of 2019 in Prof. Arcidiacono's expanded sample. Prof. Arcidiacono's Model 6 is used with interactions between race and year, disadvantaged and year, and with the exclusion of the overall rating.
[2] Mr. Kahlenberg doubles the number of disadvantaged applicants. Applicants are ranked in descending order of admission index and an equal number of applicants are admitted from each neighborhood cluster. Mr. Kahlenberg removes consideration of an applicant's race and lineage status, whether the applicant applied Early Action, whether the applicant's parents are Harvard faculty or staff, whether the applicant appeared on the Dean's or Director's interest list, whether the applicant was identified as disadvantaged, whether the applicant applied for a waiver of the application fee, whether the applicant is a first-generation college student, whether the applicant applied for financial aid, and whether the applicant is a recruited athlete. In addition, recruited athletes are assigned extracurricular and athletic ratings of 2. Mr. Kahlenberg gives a boost to disadvantaged applicants by adding to their admission index a value equal to half the value of the "athlete" coefficient in the model.
[3] This analysis reports values entirely from the predicted class. In his report, Mr. Kahlenberg reports average academic index, extracurricular rating, and personal rating values from the actul admitted class, while reporting the racial composition and share of disadvantaged students from the predicted class, under the "Status Quo" specification.