

EXHIBIT 37

**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

REBUTTAL REPORT OF DAVID CARD, Ph.D.

March 15, 2018

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1. ASSIGNMENT AND SUMMARY OF FINDINGS

1.1. Assignment

1. I have been asked to review the Rebuttal Expert Report of Peter S. Arcidiacono (“Arcidiacono Rebuttal”) and the Reply Declaration of Richard Kahlenberg (“Kahlenberg Rebuttal”) in support of the claims of the Plaintiff, Students for Fair Admissions, Inc. (“SFFA”); assess the reliability of the analyses therein; and comment on how those analyses affect (if at all) my opinions, which I previously outlined in my first report (“Card Report”).

2. As with my first report, in conducting my review of the two rebuttals, I have relied on a variety of sources of information, including the data and documents I relied on in my first expert report (summarized in Appendix A of that report). Additionally, I have reviewed all of the relevant supporting materials submitted by Prof. Arcidiacono and Mr. Kahlenberg for their rebuttals. Appendix A to this report includes an updated list of the documents and data on which I relied in forming the opinions expressed in this report.

1.2. Summary of opinions

3. In his rebuttal, Prof. Arcidiacono offers a variety of critiques of, and responses to, the analysis in my first report. While his rebuttal covers much ground, his disagreements with my analysis can be traced to a relatively simple methodological difference: My analysis is grounded in, and motivated by, the actual process that Harvard employs in making admissions decisions, based on my careful review of the available testimony and documentary evidence in the record. As I will detail in this report, Prof. Arcidiacono’s analysis, on the other hand, is grounded in a variety of misunderstandings about how Harvard’s process works, what factors Harvard values in the admissions process, and how candidates are admitted. These fundamental misunderstandings explain why Prof. Arcidiacono and I reach different conclusions, and why Prof. Arcidiacono’s admissions model yields unreliable results.

4. There should be no dispute that a statistical model that reliably assesses SFFA’s claims of bias against Asian-American applicants in this case must include as much information as possible about *the underlying process Harvard employs* in making admissions decisions, given the available data. In my first report I noted that “[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,” and that, as a result, “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.*¹ Indeed, in Sections 3 and 4 of my first report I spent more than 30 pages summarizing in detail, based on the extensive record evidence, the factors Harvard values and the process Harvard uses to collect as much information as possible regarding the many factors that drive its admissions decisions. Additionally, for each piece of information in my model, I carefully explained the reason for its inclusion and how it related to the actual decision process I was modeling.

5. In both his original report and his rebuttal, Prof. Arcidiacono takes a different approach. He models what he apparently believes Harvard's process *should* value. In his 78-page rebuttal, Prof. Arcidiacono does not refute the testimony or documents from Harvard College's Office of Admissions and Financial Aid ("Admissions Office") or from individual admissions officers regarding the core aspects of Harvard's whole-person admissions process that I rely on to develop my model. Instead, he repeatedly mischaracterizes the admissions process in a manner that misses critical aspects of how Harvard makes decisions, and then relies on those mischaracterizations as a basis for excluding critical information from the model that undermines his key findings. Most notably, he continues to focus on the relative strength of Asian-American applicants on academic dimensions while downplaying the fact—detailed repeatedly in Harvard's documents and extensively summarized in my first report—that academic excellence is the most abundant trait in Harvard's applicant pool, and that, as a result, it is not a particularly effective way for applicants to distinguish themselves. In **Section 2**, I summarize the key aspects of Harvard's admissions process that Prof. Arcidiacono has mischaracterized and/or omitted.

6. In **Section 3**, I turn to a more detailed discussion of my key methodological and factual disagreements with Prof. Arcidiacono, all of which derive from his apparent misunderstanding of how Harvard's admissions process works. Specifically, in Section 3, I explain how Prof. Arcidiacono's finding of alleged "bias" against Asian-American applicants depends entirely on his decision to exclude important pieces of information from his admissions model—including information about candidates' life experiences, interests, and family backgrounds—that the record indicates are essential to the admissions process. By excluding this critical information, he creates a problem of "missing data" or "omitted variable bias" in his models, which leads to a misleading appearance of discrimination against Asian-American applicants. As I show below, once all relevant information is included, there is no evidence of discrimination.

7. The most critical example of this problem is Prof. Arcidiacono's decision to exclude the personal rating from his model. As I detail in **Section 3.1**, Prof. Arcidiacono continues to assert that the personal rating is "biased" against Asian-American applicants and should therefore be completely

¹ Expert Report of David Card, *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College (Harvard Corporation)*, December 15, 2017 ("Card Report"), p. 47.

excluded from his admissions model. Prof. Arcidiacono’s argument for excluding the personal rating rests entirely on a set of empirical analyses that, when objectively considered, do not support his claim of bias. Specifically, Prof. Arcidiacono has constructed a model of the personal rating that finds that Asian-American applicants have lower personal ratings than White applicants, controlling for other available factors. However, as I detailed in my first report (and again in **Section 3.1** below), a critical limitation of this analysis is that Prof. Arcidiacono’s personal ratings model cannot control for all information that Harvard relies on when assigning personal ratings (including but not limited to the personal essay, the full text of teacher and guidance counselor recommendation letters, any supplemental recommendation letters, and any comments from alumni interviewers that have arrived before the personal rating is assigned). As he does elsewhere, Prof. Arcidiacono simply ignores this clear fact about Harvard’s admissions process, and asserts—contrary to the facts—that his model is sufficiently robust to reliably measure racial “bias” in the personal rating. A more objective interpretation of Prof. Arcidiacono’s personal ratings model is that it is not capable of reliably determining whether the personal rating is in fact “biased” or whether his model is simply missing critical aspects of the admissions process (e.g., the personal essay and other related information) that could explain the differences in personal ratings if available. As I explained in my first report, this is a very standard “omitted variable bias” problem that arises in statistical modeling where key pieces of information are not included in the model.

8. What is particularly striking about Prof. Arcidiacono’s claim that his personal rating model provides evidence of racial “bias” is that he reaches the opposite conclusion with regard to the differences he finds in favor of Asian-American applicants in his academic and extracurricular ratings models. Specifically, in his rebuttal, Prof. Arcidiacono argues that the positive bias in favor of Asian-American applicants that he finds in his academic and extracurricular ratings models reflects nothing more than Asian-American applicants being “stronger on unobservable characteristics” that are missing from his models.² This, of course, is the exact explanation he rejects when interpreting the negative unexplained gap between Asian-American and White applicants in the personal ratings as racial “bias,” even though (as I show in my first report) Asian-American applicants are less strong, on average, on the non-academic dimensions Harvard evaluates. For example, as I show below, White applicants are more likely than Asian-American applicants to have strong scores across the three ratings that Harvard’s interviewer handbook identifies as among the important inputs to the personal rating—the teacher rating, the guidance counselor rating, and the alumni rating. White applicants are also more likely to have strong scores across the three non-academic profile ratings (extracurricular, athletic, and personal).

9. Prof. Arcidiacono cannot selectively apply the same reasoning in opposite ways. Either

² Rebuttal Expert Report of Peter S. Arcidiacono, *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College (Harvard Corporation)*, January 30, 2018 (“Arcidiacono Rebuttal”), p. 26.

Harvard is biased *against* Asian-American applicants on the personal rating and biased *in favor* of Asian-American applicants on the academic and extracurricular ratings, or his ratings regressions reflect missing factors that are hard to measure – as he asserts about the academic and extracurricular ratings. The fact that the single rating that Prof. Arcidiacono concludes is “biased” is the rating where, on average, Asian-American applicants fare slightly less well than other groups makes clear that Prof. Arcidiacono is selectively interpreting the evidence from his models. His decision to exclude the personal rating from his overall admissions model is even more problematic when we consider that documents from Harvard’s Admissions Office identify “unusually appealing personal qualities” and “outstanding capacity for leadership” as two types of distinguishing excellence Harvard seeks, and that the personal rating is the most relevant piece of available data that captures such factors. As summarized in my first report, Harvard’s training materials for admissions officers provide numerous tangible examples of the importance placed on personal qualities in evaluations of individual candidates. Yet Prof. Arcidiacono excludes the personal rating without providing any objective evidence of bias, and asserts that his model without the personal rating is more reliable than one that includes it. Neither choice is defensible.

10. In a similar argument, Prof. Arcidiacono asserts that my inclusion of parental occupation in the admissions model is flawed because there is “no evidence in the records that Harvard’s admissions office considers parental occupation important aside from its value as a measure of SES” and because it allegedly “oscillates wildly from year-to-year.”³ As I explain in **Section 3.2** below, deposition testimony and other evidence in the record indicate that parental occupation is an important piece of information that Harvard admissions officers consider when reading applications and discussing candidates at admissions meetings. Further, of the available variables that reflect socioeconomic status in Harvard’s data, it contains the most detailed information. There is simply no basis for excluding an important piece of information that Harvard considers in its process. Prof. Arcidiacono also overstates the year-to-year fluctuations in the occupation data I rely on and fails to recognize that year-to-year fluctuations are not of concern so long as the model allows the effect of parental occupation to vary from one year to the next (as mine does). There is no objective justification for excluding this important information from the model. Prof. Arcidiacono’s methodological motivation appears to be that excluding parental occupation substantially increases the alleged disparity between Asian-American applicants and White applicants. As I explain in **Section 3.2**, Prof. Arcidiacono applies similarly flawed reasoning in arguing that staff interview ratings and the applicant’s intended career—two variables that Harvard uses in its process—should also be excluded from the model.

11. In **Section 3.3** and **Section 3.4**, I address two additional methodological flaws in Prof. Arcidiacono’s analysis, which also stem from his apparent misunderstanding of how Harvard’s

³ Arcidiacono Rebuttal, p. 6.

admissions process works. First, Prof. Arcidiacono continues to pool all the applicants who apply in different years into a single regression model, even though Harvard’s admissions process is distinct in each year. As I explain in **Section 3.3**, Prof. Arcidiacono’s approach imposes the clearly incorrect assumption that applicants from the class of, for example, 2019 are competing for slots with applicants from the class of 2014. There is simply no evidentiary or logical defense for such an assumption. The only credible methodological reason Prof. Arcidiacono offers for pooling together applicants from six different classes into a single model is that estimating a separate model for each separate year of applicants “reduces the statistical power of the sample.” As I explained in my first report and again below, by estimating a separate model for each class of applicants and then taking the average of the relevant results across all years of data, I resolve this problem with no reduction in the statistical power of the sample. In fact, the statistical power of my model—as summarized by the precision of the estimated average marginal effect of Asian-American ethnicity—is actually slightly higher than that of Prof. Arcidiacono’s pooled model.

12. Second, Prof. Arcidiacono argues that a particular set of purportedly “special” candidates (e.g., recruited athletes, lineage applicants) should be excluded from the admissions model because Harvard allegedly conducts a “special” admissions process for such candidates.⁴ As I explain in **Section 3.4**, I have seen no evidence that Harvard conducts a separate admissions process for such candidates, nor has Prof. Arcidiacono presented any such evidence. While it is true that Harvard gives a “tip” in its admissions process to candidates who have certain characteristics, that “tip” in no way guarantees their admission nor does it remove the need for such candidates to possess other characteristics valued by Harvard. For example, as I show below, even among candidates who possess the “special” characteristics, the subset who are ultimately admitted are the ones who possess many other characteristics Harvard values. Further, my admissions model shows that such candidates have stronger overall profiles and more valued characteristics than other applicants, even when their “tip” is removed. In other words, no applicant is guaranteed admission simply based on one trait—every applicant still has to compete with the larger pool on other dimensions. As with the issues discussed above, Prof. Arcidiacono’s decision to exclude these candidates from his model is not consistent with how the admissions process works, and removes important information from his model that helps quantify how Harvard makes decisions across the many characteristics it values.

13. In **Section 4**, I shift the discussion away from Prof. Arcidiacono’s critiques of my analysis, and show that when all relevant variables Harvard considers in its admissions process are included in my admissions model, I continue to find no evidence of bias against Asian-American applicants. Indeed, my model shows no evidence of bias even when I incorporate the various technical concerns raised by Prof. Arcidiacono. As part of the discussion in Section 4, I also address Prof. Arcidiacono’s new claim that the alleged bias against Asian-American applicants is not applied

⁴ Arcidiacono Rebuttal, p. 69.

to all applicants, but is instead somehow concentrated on a subset of applicants. As a conceptual matter, I discuss the implausibility of such a theory of discrimination. What is the basis of Prof. Arcidiacono's new claim? What evidence in the record supports it? Why would Harvard pursue such a complex form of discrimination? Prof. Arcidiacono does not provide answers to these questions.

14. Moreover, I show that the results I presented in my initial report demonstrating that there is evidence of a *positive* (though statistically insignificant) estimated effect of Asian-American ethnicity for two large subgroups, Asian-American women and Asian-American applicants from California, continue to hold even after I make modifications to address Prof. Arcidiacono's criticisms. These large subgroups account for nearly two-thirds of Asian-American applicants. As I discussed in my first report, this finding strongly supports my broader point that the unexplained gaps in admission rates between Asian-American and White applicants are best interpreted as reflecting differences in characteristics that are not perfectly measured by the admissions data, rather than racial bias against Asian-American applicants.

15. In **Section 5**, I turn to the question of whether race is a determinative factor in the Harvard admissions process. In his rebuttal, Prof. Arcidiacono opines that it is. His opinion is predominantly driven by the relatively large effect of race for the subset of competitive African-American and Hispanic candidates. This effect is not a new finding; I discussed it in my initial report. What I show below, however, is that the magnitude of this effect is not unique to race and, thus, cannot support the inference that race is a determinative factor in the admissions process. More specifically, what we see in the data is that, for any candidate who has a relatively strong profile, the incremental marginal effect of adding *any* additional valued characteristic to his or her profile—e.g., a strong academic or extracurricular or personal profile rating—can be relatively large, and in some cases larger than the effect of race. This pattern is exactly what would be expected given Harvard's whole-person admissions process. In order to be admitted from the highly competitive applicant pool at Harvard, any candidate must have *multiple* areas of strength in his or her profile, which means that changing any single characteristic of a candidate who is otherwise already competitive can substantially raise his or her chance of being admitted. Importantly, this feature of the process does not imply that any single characteristic on its own determines admissions decisions. In fact, the situation is just the opposite. Without being strong on multiple dimensions valued by Harvard, a candidate has little chance of admission. This is clearly evident from the large fraction of African-American and Hispanic applicants who are rejected in the admissions process. Only when a candidate reaches a certain level of overall strength can any additional characteristic help his or her candidacy significantly.

16. In **Section 6**, I turn to Prof. Arcidiacono's allegation that Harvard is imposing a floor on the African-American admission rate. As I discuss in that section, three considerations undermine

Prof. Arcidiacono's claims. First, Prof. Arcidiacono does not present persuasive facts in support of his claim that Harvard was so concerned about the single-race African-American admission rate that it chose to manipulate that rate. Indeed, his explanation for the claim has shifted between his two reports, reflecting the fact that the documentary record does not support his story. Second, the pattern in the data that Prof. Arcidiacono claims as evidence of manipulation could be explained by chance. As I discuss in Section 6 below, given that Harvard has used at least three different classifications of race (New Methodology, Old Methodology, IPEDS) during the period in question, and that each classification includes multiple racial groups, a finding that the admission rate for a racial subgroup is close to the overall admission rate is not as unusual as Prof. Arcidiacono would have one believe. Finally, as I noted in my first report, if Harvard had in fact imposed a floor on African-American admission rates, we would expect to see the relative quality of African-American students fall. Prof. Arcidiacono presents an analysis claiming that this happened. As I discuss in Section 6, his analysis contains a calculation error that, when corrected, reverses his finding.

17. In **Section 7**, I respond to several arguments from the Kahlenberg Rebuttal about whether race-neutral alternatives are a viable way for Harvard to achieve its diversity goals, while also maintaining the overall quality of its student body. As I show below, the two additional race-neutral alternatives Mr. Kahlenberg presents in his rebuttal do not allow Harvard either to achieve its diversity goals or to maintain the overall quality of the student body. Both alternatives generate a reduction in the share of the student body that is African-American and a decrease in the overall quality of the class. As I discuss in Section 7, these results are not surprising—the broad academic literature has established that race-neutral alternatives can achieve racial diversity at selective institutions only at a cost to the quality of the admitted class. None of the analyses Mr. Kahlenberg presents in his rebuttal changes the central finding of my first report: the overall profile of the student body would change significantly if Harvard ceased considering race as one factor among many.

2. A RELIABLE MODEL OF HARVARD'S WHOLE-PERSON EVALUATION PROCESS REQUIRES DETAILED INFORMATION ON THE MANY NON-ACADEMIC AND CONTEXTUAL FACTORS THAT HARVARD CONSIDERS

18. As detailed in Sections 3 and 4 of my original report, the starting point for my analysis of Harvard's admissions process is a detailed assessment of the key factors considered in that process. This assessment is necessary to ensure that my model captures as much information as possible that Harvard actually relies on when evaluating candidates.

19. Understanding the decision process is a standard methodological approach to any empirical project, and, as noted above, it is especially critical for understanding why Prof. Arcidiacono and I reach different conclusions about the key issues in this case. As I detail in this report, Prof. Arcidiacono appears to misunderstand certain aspects of Harvard's process, which leads him to exclude important pieces of information from his model.

20. Given the importance of an accurate understanding of Harvard's admissions process, in this section I provide a brief summary of the key features that I detailed in my first report. I focus on the features that will be relevant to the analysis in the remainder of this report.

2.1. Harvard's admissions process seeks to find candidates with "distinguishing excellences" across a variety of dimensions, not just academic achievement

21. The guiding principle of Harvard's admissions process is a full evaluation of each candidate's high school achievements (on many dimensions), life experiences, and personal background. As noted in my first report, this principle is succinctly described in the Admissions Office's 2014 – 2015 Interviewer Handbook ("Interviewer Handbook"), in a passage entitled "The Search for Distinguishing Excellences":

Redacted

Redacted

.⁵

22. The Interviewer Handbook then identifies some specific qualities that are common ways for a candidate to distinguish herself from the applicant pool. For example, the Interview Handbook states **Redacted**

6

23. One important fact to note about Harvard’s whole-person evaluation process, as evidenced by the list above, is that academic qualifications are just one of many factors Harvard values. In fact, traditional academic achievements like high test scores and GPAs are some of the most abundant traits in the applicant pool. For example, as I explained in my first report, there were only 1,756 domestic applicants admitted in the class of 2019, yet 2,741 applicants had a perfect SAT Verbal score, 3,450 applicants had a perfect SAT Math score, and over 8,000 applicants had a perfect GPA (Exhibit 1). In fact, the “Interviewer Handbook” estimates that **Redacted**

7

24. Because strong test scores and GPA alone are so abundant, the evaluation of academic quality extends beyond such quantitative measures. As I noted in my first report, academic evaluation also accounts for the admissions officer’s knowledge of the applicant’s high school; the high school’s curriculum; appraisals of the candidate’s academic work by Harvard faculty—referred to as faculty reads; academic honors or awards; and writing skills.⁸

⁵ Interviewer Handbook, 2014-2015, HARV00001392 – 1438 (“Interviewer Handbook”) at HARV00001400 – 01.

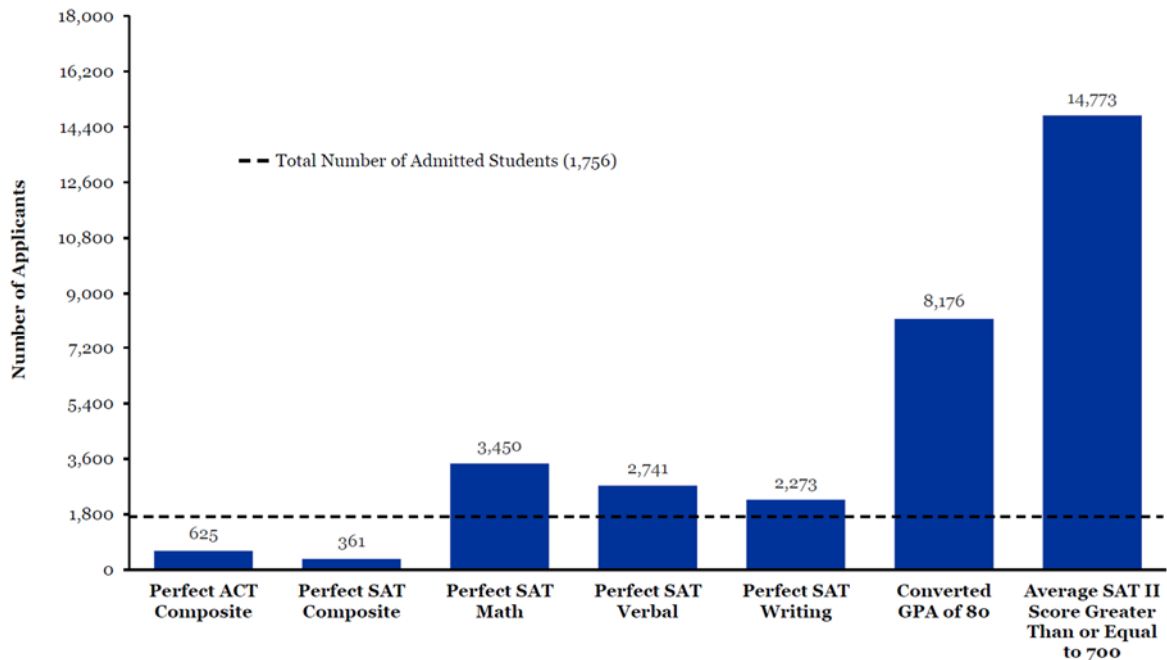
⁶ Interviewer Handbook at HARV00001401 – 02.

⁷ 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).

⁸ Card Report, p. 27

Exhibit 1

Academic excellence is abundant in Harvard's applicant pool



Source: Arcidiacono Data

Note: Data are from applicants to the class of 2019 in Prof. Arcidiacono's original expanded sample including athletes. Harvard converts applicant GPAs to a 35-80 scale.

2.2. Harvard's admissions process collects a lot of information on non-academic performance

25. As noted in my first report, in order to collect reliable information on the numerous “distinguishing excellences”—many of which are inherently difficult to quantify—Harvard employs an admissions process that emphasizes the evaluations and perspectives of multiple admissions officers, interviewers, and faculty members. Harvard describes this as “a rigorous comparative” process.⁹ It involves the collection of detailed information about each candidate’s life experience, achievements, academic potential, personality, and family/community background through a variety of interviews, essays, and relevant data (including evaluations from Harvard faculty). I described the details of the process in my first report as follows:

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

⁹ Interviewer Handbook at HARV00001408.

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. 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. My understanding is that during the full committee process, the first reader, or area 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. 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, and that discussions in subcommittee or in full Committee on a single applicant may range in length up to a half hour or more. The full Committee compares all candidates across all subcommittees (footnotes omitted).¹⁰

26. Central to Harvard's evaluation process are the four profile ratings, which are designed to capture the detailed data and information collected during the evaluation process on four key dimensions of quality Harvard values: academic, extracurricular, athletic, and personal. As detailed in my first report, Harvard's admission data on profile ratings bear out the importance of non-academic strength in Harvard's process. Below are several important patterns in the admission data discussed in my first report that demonstrate the value Harvard places on non-academic qualities:

- **Non-academic skills are scarce:** “[A]pplicants 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)

¹⁰ Card Report, pp. 24–25.

distinguish applicants in the pool much more effectively than a high academic rating”¹¹

- **Non-academic skills explain admissions decisions better than academic skills:** “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.... 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. 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” (footnote omitted).¹²
- **Being multi-dimensional is important:** “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.”¹³
- **Athletic rating is important:** “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%, [for domestic applicants], and is the same as the admission rate of applicants with an academic rating of 2. Further, as shown above, receiving a rating

¹¹ Card Report, pp. 28–29.

¹² Card Report, pp. 29–30.

¹³ Card Report, p. 30.

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” (footnote omitted).¹⁴

27. Despite these facts about Harvard’s admissions process, Prof. Arcidiacono has repeatedly focused on academic achievement as the most important characteristic in the admissions process. For example, in both of his reports Prof. Arcidiacono employs Harvard’s Academic Index as a general measure of quality for applicants to Harvard. (Harvard’s Academic Index is a value which summarizes an applicant’s strength across SAT scores, ACT scores, and grades (GPA).)¹⁵ In fact, in his first report and again in his rebuttal, he offered an analysis that predicted how Harvard’s class would look if it *only* considered Academic Index.¹⁶ This type of analysis does not reflect Harvard’s process, and, as I will detail below, is an important reason why Prof. Arcidiacono’s claim of “bias” against Asian-American applicants is flawed. The fact that Prof. Arcidiacono chose to present such an analysis underscores his fundamental misunderstanding of Harvard’s process.

2.3. Asian-American and White applicants possess different qualifications and backgrounds, on average, across a variety of dimensions

28. SFFA’s and Prof. Arcidiacono’s core theory of racial bias against Asian-American applicants centers on Prof. Arcidiacono’s conclusion that, on average, Asian-American applicants are academically stronger than applicants of other races, but they are admitted at a lower rate than White applicants. This theory ignores two critical facts: First, strong academic performance is just one factor in the process, and is also one of the most abundant characteristics in the applicant pool—that is, it does little to distinguish some applicants from others. Second, Asian-American applicants are, on average, not as strong as White applicants on several important non-academic measures. As detailed in my first report, the data show that, while Asian-American applicants have stronger average academic measures, they are weaker on average on athletic and personal ratings, less likely to be strong on multiple ratings, and less likely to have high ratings across all three non-academic ratings taken together. Exhibit 2 and Exhibit 3 below report the same data as in my first report.

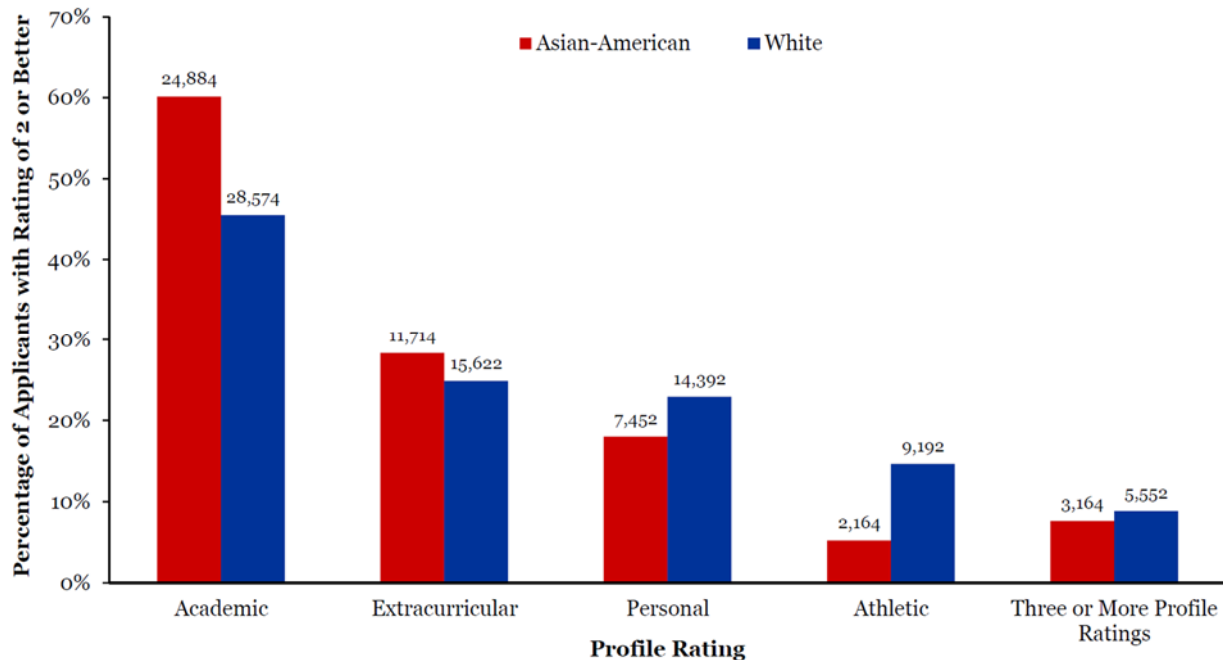
¹⁴ Card Report, p. 31. It is worth noting that, in his rebuttal, Prof. Arcidiacono continues to make the incorrect assertion that athletic rating is less important than other ratings. Prof. Arcidiacono states, “the athletic rating is not as important to the admissions decision as the other ratings once recruited athletes are removed” (Arcidiacono Rebuttal, p. 31). As shown above, Harvard’s admissions data directly contradict this statement.

¹⁵ Ivy League AI Calculator Information 20051.xlsx, HARV00001895, Tab “IVY LEAGUE AI 2005-2006.”

¹⁶ Expert Report of Peter S. Arcidiacono, *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College (Harvard Corporation)*, October 16, 2017 (“Arcidiacono Report”), pp. 44–45; Arcidiacono Rebuttal, p. 13.

Exhibit 2

White and Asian-American applicants excel in different dimensions



Source: Arcidiacono Data

Note: Data are from applicants to the classes of 2014 – 2019 in Prof. Arcidiacono’s original expanded sample including athletes. Ratings of 2- and above are considered “2 or Better” in this analysis. +/- rating designations were introduced beginning with the class of 2019.

Exhibit 3

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

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 Prof. Arcidiacono’s original expanded sample including athletes.

29. In addition to differences in non-academic strength, there are also average differences

between White and Asian-American applicants (i.e., differences between Asian-American and White applicants (on average)) on numerous other factors Harvard weighs in its admissions decisions, including proxies for life experience and interests like parental occupation, intended major, intended career, geography, and high school.¹⁷

30. In Section 3, I analyze the differences between Asian-American and White applicants in more detail, when I address Prof. Arcidiacono's claim that the differences in personal ratings observed in Harvard's sample are a result of racial bias, rather than differences in the underlying characteristics and backgrounds, on average, between the two groups. As I explain in that section, an objective analysis of the many average differences between Asian-American and White applicants does not support Prof. Arcidiacono's conclusion of bias. Rather, it supports a much simpler conclusion—while the set of Asian-American high-school students who apply to Harvard tend on average to be slightly stronger than the set of White applicants in academic respects, they tend to be weaker in non-academic dimensions.

¹⁷ Throughout my report, I use the term “average differences” to refer to differences in the average level of a given attribute across groups.

3. PROF. ARCIDIACONO'S KEY CRITICISMS OF MY ADMISSIONS MODEL REFLECT A MISUNDERSTANDING OF HOW HARVARD'S ADMISSIONS PROCESS WORKS

31. The different conclusions that Prof. Arcidiacono and I reach with regard to SFFA's claim of alleged bias against Asian-American applicants can be explained by three critical methodological errors in Prof. Arcidiacono's analyses. First, Prof. Arcidiacono excludes several variables key to Harvard's admissions process—in particular, the personal rating, parental occupation, intended career, and staff interview ratings—claiming that that they are biased and/or unreliable. Second, Prof. Arcidiacono pools together applicants from different admissions cycles into a single admissions model. Third, Prof. Arcidiacono excludes data from several categories of applicants—lineage applicants, recruited athletes, children of Harvard faculty and staff, and applicants on the Dean's or Director's interest lists—under the erroneous assumption that they are subject to a separate admissions process that is free of the alleged bias Prof. Arcidiacono's flawed model purports to show.

32. As I explain below, each of these key methodological choices by Prof. Arcidiacono stems from an incorrect (or incomplete) view of how Harvard's admissions process works, and all of them lead to a model that focuses too much on academic achievement and ignores important non-academic factors. The unexplained gap in admissions in Prof. Arcidiacono's models reflects a standard “omitted variable bias” that arises when important variables are excluded from a statistical model.¹⁸ This type of “omitted variable bias” is such a common methodological problem in econometric analysis that a popular textbook describes it as the first issue that a researcher should think about.¹⁹ It occurs whenever a regression model omits a control variable that is correlated with the independent variable of interest (in this case, race) and influences the outcome variable (in this case, admissions). It is problematic because it causes the model to misattribute to other independent variables the effect on the outcome actually caused by the omitted variable.

33. For example, suppose that younger employees in a firm are concerned that they are paid less than older employees due to some form of bias by their employer. And suppose that the

¹⁸ 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 in 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...”).

¹⁹ 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.”).

employer's pay guidelines identify two attributes of each employee that affect pay: the employee's level of education, and his or her number of years of experience in the occupation. In this example, the outcome variable is the employee's salary, and the independent variable of interest is his or her age. If a regression controls only for the employee's age and education—but not his or her number of years of experience—then the regression may misattribute to the employee's age an effect on salary that is actually due to the employee's number of years of experience. That is because the number of years of experience is correlated with both the employee's age and his or her salary.

34. The record makes clear that Prof. Arcidiacono's model is missing key variables and is therefore flawed. Further, as I showed in my first report (and as I show again in Section 4 of this report), when all of the information Harvard relies on in making its admissions decisions is included in the admissions model, there is no statistical evidence that Asian-American applicants are being admitted at lower rates than White applicants.

3.1. The personal rating is an important factor in admissions decisions, and excluding it from the admissions model is not justified

35. As detailed in my first report, Prof. Arcidiacono's claim that the personal rating is biased against Asian-American applicants is not supported by his own analysis. In his rebuttal, Prof. Arcidiacono once again asserts that the personal rating is biased against Asian-American applicants, pointing (once again) to the unexplained gap between White and Asian-American applicants in his personal rating regression, i.e., the gap that remains after controlling for the other candidate characteristics that are included in his model.

36. Prof. Arcidiacono provides two arguments for why the unexplained gap in his personal ratings regression is evidence of racial bias. First, he argues that his personal ratings regression is reliable because it has a high explanatory power by academic standards. Second, he argues that there is no alternative explanation for the unexplained gap because there is no evidence that Asian-American applicants are weaker, on average, on the observable factors that affect the personal ratings.²⁰ In what follows, I address both arguments and explain why, despite his claims to the contrary, (a) his personal ratings regression is missing key factors that affect the rating; (b) it is reasonable to conclude that Asian-American applicants are weaker, on average, on those missing factors; and (c) as a result, the unexplained gap is not evidence of bias.

3.1.1. Prof. Arcidiacono's personal ratings regression is missing critical information

37. I start with Prof. Arcidiacono's claim that his personal ratings regression reliably captures

²⁰ Arcidiacono Rebuttal, pp. 22–23, 26–27.

relevant factors that drive the personal rating, and thus reliably measures the alleged “bias” against Asian-American applicants.

38. In my first report, I argued that Prof. Arcidiacono’s personal ratings regression “cannot reliably explain the assignment of personal ratings” because (a) it had a relatively low Pseudo R-Squared,²¹ and (b) it suffered from omitted variable bias due to the omission of the personal essay and other difficult-to-measure factors that affect the personal rating.²² In response to my criticisms, Prof. Arcidiacono cites an academic paper from 1979 by Daniel McFadden that indicates that the Pseudo R-Squared of Prof. Arcidiacono’s personal ratings regression (0.28) is sufficiently high to be considered an “excellent fit.”²³ He also offers some discussion and analysis of the predictive power of his personal ratings regression.²⁴

39. While I have no major disagreement with the paper he cites, or the calculations he presents,²⁵ I believe that Prof. Arcidiacono’s response entirely misses the broader point of my original critique. Most importantly, even a model that has a relatively high Pseudo R-Squared still may suffer from omitted variable bias in estimating the effect of Asian-American ethnicity. In fact, Prof. Arcidiacono himself recognizes this principle. For example, when discussing his own academic rating regression—which has a Pseudo R-Squared (0.56) that is nearly *double* that of his personal rating regression (0.28)—Prof. Arcidiacono explains that the differences across racial groups in academic ratings capture “unobservable characteristics” outside of his model, not racial bias.²⁶ In other words, he believes his academic rating model, with a Pseudo R-Squared of 0.56, suffers from omitted variable bias. A second factor, however, is that the risk of omitted variable bias is larger when the model has lower explanatory power. This is widely understood in the academic literature, and implies that Prof. Arcidiacono’s personal rating model is even more vulnerable to omitted

²¹ As noted in my first report, Pseudo R-Squared 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.

²² Card Report, pp. 69–70.

²³ Arcidiacono Rebuttal, p. 23.

²⁴ Arcidiacono Rebuttal, pp. 23–25.

²⁵ I note, however, that the McFadden paper that Prof. Arcidiacono relies on was written in 1979, when access to, and computing power sufficient to analyze, the type of detailed microdata analyzed in this case did not exist. In modern empirical analyses—particularly where, as here, voluminous data are available—the Pseudo R-Squared of Prof. Arcidiacono’s personal ratings regression of 0.28 would not be considered strong.

²⁶ Arcidiacono Rebuttal, p. 26.

variable bias than his academic rating model.²⁷

40. The key issue with Prof. Arcidiacono's personal ratings regression, therefore, is not that its Pseudo R-Squared value is lower than might be optimal, but that the model is missing various factors that inform the personal rating that are not quantifiable and thus are not observed in the data. For example, the model is missing an assessment of the applicant's personal essay. As I explained in my first report, Harvard's Interviewer Handbook explicitly identifies information in the personal essay as a consideration central to the personal rating,²⁸ as does testimony from numerous admissions officers.²⁹ Prof. Arcidiacono's regression also includes only limited and incomplete summary information from the teacher and guidance counselor reports. For example, available application files produced in this case indicate that many applicants have recommendation letters from more than two teachers and/or supplementary letters of reference from figures like research supervisors or extracurricular instructors, even though such information is not reflected in the database.³⁰ The available applications also indicate that teacher and guidance counselor letters often review both academic and personal qualities, but are summarized by Harvard admissions officers using a single

²⁷ Emily Oster, "Unobservable Selection and Coefficient Stability," Brown University and NBER Working Paper #19054, August 9, 2016, p. 3 ("The key observation is that the quality of the control is diagnosed by how much of the variance in the outcome is explained by its inclusion or, equivalently, how much the R-squared moves when the controls are introduced. Omitted variable bias is proportional to coefficient movements, but only if such movements are scaled by the change in R-squared when controls are included.").

²⁸ Interviewer Handbook at HARV00001401 **Redacted**

²⁹ 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"), p. 80 ("Q. Okay. So for the last category, the [personal qualities]—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.").

³⁰ For example, application HARV00079421 – 75 contains three teacher recommendations. As evidenced by the reader's notes at HARV00079422, all three letters were taken into consideration when reviewing the application: "Support prose is very nice; SSR says she is the best in the class, T3 says best in 13 years, and T2 says one of the best in 20 years. There are noticeable checks down for concern for others on both T1 and T2, though, and many references to how driven she is." Application HARV00079519 – 63 contains three teacher letters (at HARV00079543 – 9), as well as a supplementary letter of support from the school's Club Faculty Advisor (at HARV00079554 – 5). Application HARV00079476 – 518 also contains three teacher recommendations (at HARV00079500 – 6), as well as a recommendation from the applicant's Tae Kwon Do instructor (at HARV00079510 – 1). As another example, application HARV00079325 – HARV00079420 contains two recommendations from teachers (at HARV00079349 – 55), as well as a letter of recommendation from the supervisor of a lab at **Redacted** where the applicant conducted research (at HARV00079381 – 2).

rating from which it is impossible to separate the academic qualities from the personal qualities.³¹

41. The fact that key factors central to the determination of the personal rating are missing from Prof. Arcidiacono's personal rating regression, and the fact that it has a *relatively* weak Pseudo R-Squared (as compared to his academic rating regression), mean that Prof. Arcidiacono's personal ratings regression cannot establish that differences across ethnic groups in the personal rating are caused by racial bias (as he claims), rather than by average differences in other personal characteristics not included in the database that Prof. Arcidiacono and I analyze.

42. What is particularly striking about Prof. Arcidiacono's claim of bias in the personal rating is how he reaches the opposite conclusion for the academic and extracurricular ratings, even when the pattern of empirical evidence is the same. For example, Prof. Arcidiacono interprets the unexplained racial gaps in his academic and extracurricular ratings that *favor* Asian-American applicants as evidence that his model is missing important information, rather than that Harvard is biased in favor of Asian-American applicants. However, when faced with an unexplained gap in the *personal* rating regression (that favors White applicants rather than Asian-American applicants), he rules out this same "unobserved characteristics" explanation and instead jumps to the conclusion that there is bias against Asian-American applicants. In light of the known factors that inform the personal rating but are not captured in Prof. Arcidiacono's personal rating model, and the relatively low explanatory power of his personal rating model, it is indefensible for Prof. Arcidiacono to claim that the disparity in personal ratings between Asian-American and White applicants is evidence of bias, while simultaneously arguing that the (converse) disparity in his academic ratings model is due to omitted variable bias.

43. Prof. Arcidiacono cannot selectively apply the same reasoning in different ways. Either his ratings regressions reflect missing factors that are hard to measure—as he asserts about the academic and extracurricular ratings—or they reflect a complex (and unusual) form of racial discrimination whereby Harvard favors Asian-American applicants on academic and extracurricular

³¹ For example, see the teacher and guidance counselor recommendations in application HARV00079325 – HARV00079420. A letter from the applicant's math teacher describes both the student's mathematical aptitude, as well as the student's personal qualities, such as his willingness to help other students and his "politeness and respect for his fellow man, as well as his sense of humor" (at HARV00079351). Note that the reader's summary of the guidance counselor's letter mentions both academic qualities like intelligence and curiosity, as well as more personal descriptors: "GC describes his 'insatiable curiosity,' and calls him the most well-mannered, pleasant, and intelligent student ever" (at HARV00079386). As another example, see application HARV00079812 – 52. The applicant's letters showcase both his academic achievements and personal qualities, something both readers comment on. One reader writes: "Teachers praise his natural intelligence but also speak to his habit of helping his peers and his sense of humor and relaxed personality outside of academics. There's a great deal of raw talent and interest here, and I imagine he would use this place well," and the other writes "[Redacted] is highly respected by his teachers for his academic strength and good PQ's (They say he has a great sense of humor, though he is very focused on academics.)" (at HARV00079813).

dimensions and disfavors them on personal dimensions.

44. Prof. Arcidiacono's inconsistent interpretation of his own ratings models is a key issue that I identified in my first report as evidence against his conclusion of bias in the personal rating process. As I noted in that report:

[S]uch a pattern calls into question whether the effects [Prof. Arcidiacono's] 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.³²

3.1.2. The data show that, on average, Asian-American applicants are weaker on non-academic factors that affect the personal rating

45. The explanation Prof. Arcidiacono offers for his selective interpretation of the alleged bias across the different ratings regressions is that "the case for discrimination is very strong when a group of applicants is strong on the observed characteristics associated with a particular rating, yet faces a penalty."³³ Prof. Arcidiacono then argues that there is no evidence that Asian-American applicants are weaker, on average, on factors associated with the personal rating, and thus that it is proper to infer discrimination. Yet a key driver of this conclusion is Prof. Arcidiacono's focus on Asian-American applicants academic qualifications, rather than on the non-academic factors that affect the personal rating. This logic does not make sense because, as discussed above, the unobservable factors that are missing from Prof. Arcidiacono's personal ratings regression are not academic factors. They are non-academic factors like the personal essay, other recommendation letters, and any other discussion that informs a candidate's personal quality. Thus, the fact that Asian-American applicants are stronger on academic factors is not sufficient evidence to conclude that they are also stronger on *unobservable* factors that affect the personal rating.

46. As I detailed in my first report, there are three key patterns in the data that indicate that,

³² Card Report, p. 71.

³³ Arcidiacono Rebuttal, p. 26.

on average, Asian-American applicants are weaker on non-academic dimensions.

- First, if we look at the four profile ratings Harvard relies on, we see that, while many Asian-American applicants are stronger on academic qualifications, they are, on average, weaker across all non-academic measures. See Exhibit 3 above, which I have reproduced from my first report.
- Second, the patterns in Prof. Arcidiacono's own personal ratings regression strongly suggest that Asian-American applicants are on average weaker across non-academic measures. In those regressions, the estimated negative effect of Asian-American ethnicity shrinks as he adds non-academic factors. Specifically, the logit coefficient falls by nearly 30 percent, from -0.547 to -0.391, when he adds controls for neighborhood and school background and for the relevant ratings that feed into the personal rating, like the teacher, guidance counselor, and alumni ratings.³⁴ This is a critically important finding because, as noted above, the types of information missing from the personal rating regression are non-academic in nature. Thus, the fact that the measured disparity in ratings between Asian-American and White applicants shrinks as additional non-academic factors are added to the ratings model suggests that the disparity would shrink further if other non-academic factors (such as information from the personal essay) could be added. In fact, it is well understood in the academic literature that this pattern of a declining effect when additional controls are added to the model is a red flag that other unobserved factors are potentially correlated with the variable of interest.³⁵ In this case, it suggests that unobserved factors are correlated with Asian-American ethnicity in a way that leads the model to overstate the negative effect of Asian-American ethnicity.

³⁴ Arcidiacono Rebuttal, Appendix D, Table B.6.7R.

³⁵ Emily Oster, "Unobservable Selection and Coefficient Stability," Brown University and NBER Working Paper #19054, August 9, 2016, p. 3.

- Third, the non-academic factors in Prof. Arcidiacono’s own admissions model contradict his claim that there is no evidence that Asian-American applicants are weaker, on average, on non-academic dimensions. I created a non-academic admissions index that summarizes the collective admissions strength of each candidate across all non-academic factors in Prof. Arcidiacono’s model, using the same methodology Prof. Arcidiacono used to create what he called an “admissions index.”³⁶ Using this non-academic admissions index, I found that the Asian-American applicants were less likely than White applicants to be in the top half, as well as the top decile, of this index.³⁷

47. In his rebuttal, Prof. Arcidiacono attempts to counter these analyses with new arguments that are misleading or factually incorrect. First, Prof. Arcidiacono asserts that the scores Asian-American applicants receive on the key ratings that inform the personal rating (alumni, teacher, and counselor ratings) “differ significantly” from the overall personal rating scores assigned to Asian-American applicants.³⁸ In response to this claim I have analyzed the sum of the ratings from alumni interviewers, teachers, and guidance counselors, and compared them across Asian-American and White applicants. The best possible ratings sum is 5 because there are five ratings (two teacher ratings, one guidance counselor rating, and personal and overall ratings from an alumni interviewer) and ratings vary from 1 to 5 (the lower the rating, the stronger it is, with a rating of 1 being the best). For example, an applicant who received teacher, guidance counselor, and alumni ratings of 1, 2, 2, 2, and 1 would have a ratings sum of 8. The sum can be viewed as an overall summary measure of the strength of each candidate as reflected in the interviews and materials submitted by external reviewers. If Prof. Arcidiacono’s claim that Asian-American and White applicants are of similar quality on these ratings is true, then we should not see any major differences between these two groups.

48. As shown in Exhibit 4, this is simply not the case. For a given level of academic ratings, Asian-American applicants are *less likely* than White applicants to receive strong ratings collectively across these five ratings. For example, Exhibit 4 shows that among applicants with an academic rating of 2, White applicants are more likely to have strong scores (i.e., a lower sum) than Asian-American applicants, indicating that they are stronger on average than Asian-American applicants on these dimensions, which inform the personal rating.³⁹ This is demonstrated by the fact that the

³⁶ SAT, GPA, Academic Index, academic rating, and academic rating interaction variables are considered academic factors for purposes of constructing this index.

³⁷ Card Report, p. 39, Exhibit 10.

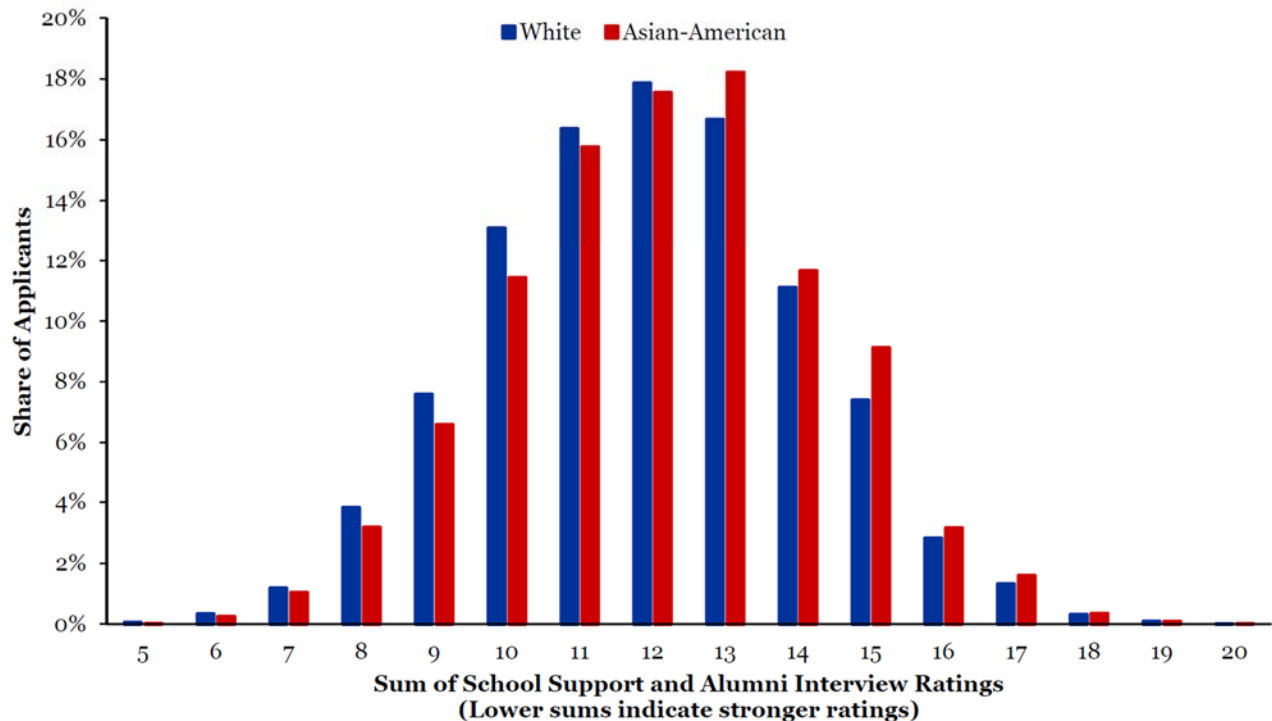
³⁸ Arcidiacono Rebuttal, p. 14.

³⁹ This same pattern is observed for other academic ratings as well. See workpaper.

distribution for Asian-American applicants (represented by red bars) is shifted right (i.e. toward higher sums) relative to the distribution for White applicants (represented by blue bars). Exhibit 5 shows that the same pattern is true for other levels of the academic rating. Specifically, it shows the share of White applicants and the share of Asian-American applicants who have very strong school support and alumni interview ratings (measured as having a ratings sum of 11 or less) for each category of academic rating. Among applicants with an academic rating of 2, 42% of White applicants have a ratings sum of 11 or less, compared to 38% of Asian-American applicants, with similar gaps among applicants with other competitive academic rating levels.⁴⁰

Exhibit 4

Among applicants with an academic rating of 2, White applicants tend to have stronger school support and alumni ratings than Asian-American applicants



Source: Augmented Arcidiacono Data

Note: Data are from applicants to the classes of 2014 – 2019 in Prof. Arcidiacono’s expanded sample including athletes.

⁴⁰ Prof. Arcidiacono states in his report that “African-American and Hispanic applicants have observed characteristics associated with lower [worse] personal ratings yet receive a preference in their personal ratings” (Arcidiacono Rebuttal, p. 27). Again, Prof. Arcidiacono is basing this claim primarily upon an analysis of the Academic Index, not the non-academic characteristics (such as the school support and alumni interview ratings) that actually determine the personal rating. An examination of the sum of school support and alumni interview ratings for African-American applicants shows that, contrary to Prof. Arcidiacono’s assertion, they actually have observed characteristics associated with *stronger* personal ratings. See workpaper.

Exhibit 5

For a given academic rating, White applicants tend to have stronger school support and alumni ratings than Asian-American applicants

Academic Rating	Share of Applicants with School Support and Alumni Interview Ratings that Sum to 11 or Less		
	All	White	Asian-American
1. 1	87%	90%	85%
2. 2	41%	42%	38%
3. 3	18%	19%	15%
4. 4	6%	5%	5%
5. 5	3%	2%	2%

Source: Augmented Arcidiacono Data

Note: Data are from applicants to the classes of 2014 – 2019 in Prof. Arcidiacono’s expanded sample including athletes.

49. It is important to note that Harvard’s Interviewer Handbook specifically states that **Redacted**
Redacted

The Handbook identifies **Redacted**

as important sources in identifying applicants with **Redacted**
Redacted

⁴¹ In other words, when looking at the observable ratings that both Harvard and Prof. Arcidiacono identify as relevant inputs into the personal rating, White applicants are collectively stronger than Asian-American applicants. Under Prof. Arcidiacono’s own logic, this fact provides an alternative explanation for the unexplained gap in personal ratings Prof. Arcidiacono finds. Because Asian-American applicants are weaker on average on key *observable* factors that affect the personal rating, it is entirely plausible that the unexplained gap in the personal rating reflects differences in *unobservable* factors that are missing from the personal ratings regression, rather than racial bias against Asian-American applicants.

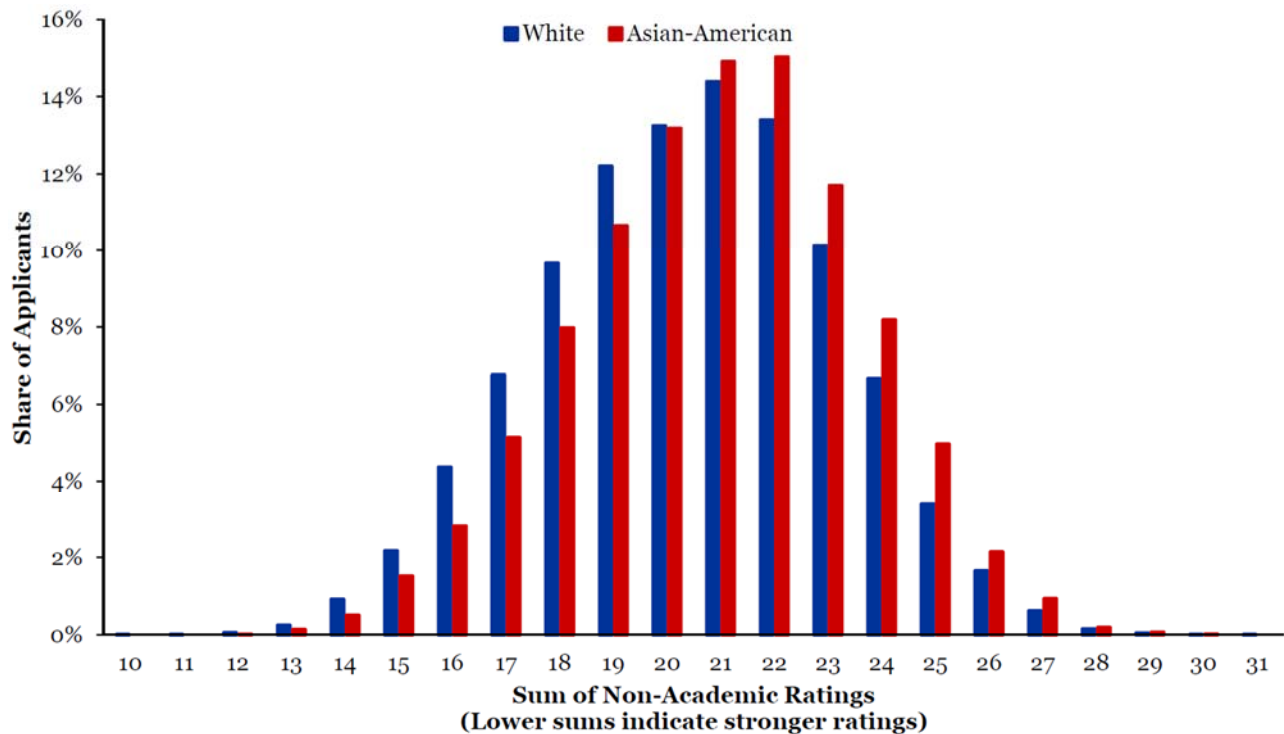
50. If I measure non-academic qualities more broadly, summing not only school support and alumni interview ratings but also the extracurricular, personal, and athletic ratings, Asian-American applicants are on average even weaker relative to White applicants. In this case, the ratings sum consists of a sum over eight ratings, where in each case a rating of 1 is the best possible rating, so the best possible ratings sum is 8. An applicant who received a rating of 2 on all eight ratings would have a sum of 16. Exhibit 6 shows the distribution of ratings sums over these eight ratings for Asian-

⁴¹ Interviewer Handbook at HARV00001401.

American and White applicants who received an academic rating of 2, and Exhibit 7 shows the share of Asian-American and White applicants who have a ratings sum of 18 or less by academic rating. Again we see that Asian-American applicants are weaker on non-academic qualities, i.e., have higher ratings sums than White applicants.⁴² Again this is demonstrated by the fact that the red distribution (that of Asian-American applicants) is shifted right, i.e. toward larger ratings sums, relative to the blue distribution (that of White applicants). And, again, because the factors that are missing from the personal rating regression are non-academic in nature, these differences in non-academic factors provide an alternative explanation for the unexplained gap Prof. Arcidiacono finds in his personal rating regression.

Exhibit 6

Among applicants with an academic rating of 2, White applicants have stronger non-academic ratings (school support, alumni, and profile other than academic)



Source: Augmented Arcidiacono Data

Note: Data are from applicants to the classes of 2014 – 2019 in Prof. Arcidiacono’s expanded sample including athletes.

⁴² The pattern observed in Exhibit 6 also holds for other academic ratings. The patterns observed in Exhibit Exhibit 6 and Exhibit Exhibit 7 also hold if I exclude the personal rating. See workpaper.

Exhibit 7

For a given academic rating, White applicants have stronger non-academic ratings (school support, alumni, and profile other than academic)

		Share of Applicants with Non-Academic Ratings that Sum to 18 or Less		
Academic Rating		All	White	Asian-American
1.	1	62%	71%	58%
2.	2	21%	24%	18%
3.	3	9%	10%	6%
4.	4	2%	2%	1%
5.	5	0%	0%	1%

Source: Augmented Arcidiacono Data

Note: Data are from applicants to the classes of 2014 – 2019 in Prof. Arcidiacono’s expanded sample including athletes.

51. In his rebuttal, Prof. Arcidiacono also challenges my argument that adding more non-academic variables to his personal ratings regression reduces the unexplained gap in personal ratings between Asian-American and White applicants. Specifically, he claims that it is not “universally true” that adding controls to his personal ratings regression leads to a lower estimated marginal effect of Asian-American ethnicity, and notes that “adding all the controls basically resulted in the same penalty for Asian-American applicants as in the model with no controls.”⁴³ The critical flaw in this logic is that Prof. Arcidiacono includes *academic* variables in his analysis.⁴⁴ What matters is not whether it is “universally true” that all controls shrink the unexplained gap. What matters is whether the crucial information omitted from the model that is known to inform the personal rating (e.g. the personal essay, additional recommendation letters, etc.) would shrink the unexplained gap. The most reliable way to test how such missing information affects the unexplained gap in personal ratings is to test how similar non-academic variables that we can observe in the data impact the unexplained gap. As noted, above, Prof. Arcidiacono’s own analysis shows that the non-academic variables that are important to the personal rating (like the teacher, guidance counselor, and alumni interview ratings)

⁴³ Arcidiacono Rebuttal, p. 27.

⁴⁴ There is another flaw in this analysis, which is that Prof. Arcidiacono adds interaction terms to his model as he moves from his model with no controls (model 1) to his model with all controls (model 5). By adding these interaction terms, he changes the group of applicants the Asian coefficient applies to. For example, his model 1 Asian-American coefficient represents the effect of Asian-American ethnicity for all Asian-American applicants but his model 5 coefficient represents the effect of Asian-American ethnicity for only Asian-American applicants who are male, not flagged as disadvantaged, and not recruited athlete, lineage, Dean’s or Director’s list, or children of Harvard faculty and staff applicants.

shift the unexplained gap towards zero.⁴⁵ Thus, it is likely that more non-academic variables would have the same effect. Prof. Arcidiacono's argument misses the point.

52. Additionally, in his rebuttal, Prof. Arcidiacono responds to the analysis from my first report that compares Asian-American and White applicants on the "non-academic" index from Prof. Arcidiacono's admissions model. Specifically, in Table 3.1.N he presents a "corrected" version of my analysis, which he claims shows that Asian-American applicants are just as strong as White applicants on non-academic dimensions.⁴⁶ However, his results are driven by his exclusion from the sample of many of the strongest White applicants: lineage applicants, recruited athletes, applicants on the Dean's or Director's interest lists, and children of Harvard faculty and staff. He refers to these excluded applicants as "specially recruited" applicants, but I will refer to them as ALDC (Athlete, Lineage, Dean/director list, Children of faculty/staff) applicants. Comparing the full sample of Asian-American and White applicants provides further evidence that White applicants are stronger, on average, on non-academic dimensions.⁴⁷

53. As demonstrated in the first panel of Exhibit 8, once ALDC applicants are included in the sample, White applicants are more likely than Asian-American applicants to fall in the top deciles of the non-academic admissions index. For example, if we look at Row 6 of the first panel, we see that 12.03% of White applicants are in the highest decile of the non-academic index, whereas only 7.75% of Asian-American applicants are. The highest decile of the non-academic index represents the group of applicants with the strongest chance of admissions based on all non-academic variables in the admissions model. The fact that White applicants are more likely to be in that group indicates that White applicants are stronger than Asian-American applicants on non-academic dimensions. This is true even if I accept Prof. Arcidiacono's other modifications, such as removing the effect of the "tips" associated with being an ALDC applicant (see second panel of Exhibit 8), removing the effect of the personal rating (see third panel of Exhibit 8), or doing both (see fourth panel of Exhibit 8). In each case, White applicants are more likely to be strong on non-academic dimensions, i.e., fall in the top deciles of the non-academic admissions index.

⁴⁵ Another way to see that additional non-academic variables help shrink the unexplained gap is to take Prof. Arcidiacono's personal ratings regression and estimate it year-by-year. When I do this, I can add additional variables to the model in later years that Prof. Arcidiacono omits from his model because they do not exist for all years (as well as add additional non-academic factors controlled for in my model but not in his). Doing this, I find that the unexplained gap in ratings between Asian-American and White applicants shrinks even further. Using Prof. Arcidiacono's preferred activities measures instead of mine in the model described above also causes the unexplained gap to shrink even more. See workpaper.

⁴⁶ Arcidiacono Rebuttal, pp. 29–30.

⁴⁷ This conclusion is supported by Prof. Arcidiacono's own analysis. In the calculations performed by Prof. Arcidiacono for appendix tables 7.5R and B.6.13R of his rebuttal, he also created versions of these tables in the same manner as I describe above. In each case, his analysis shows White applicants are stronger than Asian-American applicants on non-academic dimensions (SFFA-HARVARD 0002359_admissionsLogitsIndices.do).

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

Non-Academic Admissions Index Decile	White	Asian-American	African-American	Hispanic
<u>Without Removing Additional Effects</u>				
1. 5 or lower	46.46%	51.80%	55.27%	54.33%
2. 6	10.10%	10.35%	9.04%	9.48%
3. 7	10.12%	10.53%	9.00%	9.26%
4. 8	10.47%	10.10%	8.85%	8.90%
5. 9	10.81%	9.47%	9.06%	9.18%
6. 10	12.03%	7.75%	8.79%	8.85%
<u>Remove Effect of ALDC “Tips”</u>				
7. 5 or lower	46.98%	51.28%	55.04%	53.81%
8. 6	10.20%	10.24%	8.95%	9.42%
9. 7	10.31%	10.25%	8.82%	9.39%
10. 8	10.69%	9.98%	8.80%	8.58%
11. 9	10.80%	9.56%	9.02%	9.02%
12. 10	11.03%	8.69%	9.37%	9.77%
<u>Remove Effect of Personal Rating</u>				
13. 5 or lower	46.45%	51.59%	55.70%	54.63%
14. 6	10.36%	10.14%	9.02%	9.16%
15. 7	10.30%	10.19%	8.90%	9.27%
16. 8	10.34%	10.28%	9.13%	8.96%
17. 9	10.61%	9.84%	8.76%	9.02%
18. 10	11.94%	7.96%	8.50%	8.96%
<u>Remove Effect of Personal Rating and ALDC “Tips”</u>				
19. 5 or lower	47.02%	50.92%	55.42%	54.20%
20. 6	10.46%	10.02%	8.89%	9.14%
21. 7	10.59%	9.91%	8.79%	9.06%
22. 8	10.53%	10.02%	9.12%	8.77%
23. 9	10.84%	9.69%	8.64%	8.96%
24. 10	10.56%	9.42%	9.14%	9.88%

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 expanded sample including athletes. The non-academic admissions index is constructed using the updated approach put forth by Prof. Arcidiacono in Tables 7.4R and 7.5R in Appendix C of his rebuttal report. The shares within each panel for a given race sum to 100%.

54. Prof. Arcidiacono also attempts to rebut my analyses of the personal rating by claiming

that an internal analysis by OIR finds evidence consistent with his analysis. Specifically, he asserts that, “[u]sing data over ten years, OIR found that Harvard’s admissions officers assigned substantially lower personal ratings to Asian-American applicants versus white applicants, especially when compared to the ratings assigned by teachers, counselors, and alumni interviewers.”⁴⁸ As I described in my first report, Prof. Arcidiacono’s characterization of OIR’s findings is wrong. OIR did not in fact reach any conclusions about bias in Harvard’s process. OIR described its analysis of differences between White and Asian-American applicants as a “basic” analysis, and specifically noted that it could not account for many factors that it could not measure, like the personal essay, context variables, and socioeconomic status. Indeed, one important advantage of my model is that it controls for these types of differences better than either the preliminary and incomplete model used by OIR, or the incomplete model advocated by Prof. Arcidiacono. As I explained in my first report:

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” (footnote omitted).⁴⁹

⁴⁸ Arcidiacono Rebuttal, p. 16.

⁴⁹ Card Report, p. 66. Deposition testimony corroborates the idea that OIR researchers viewed their research as incomplete/preliminary. For example, see Deposition of Erica Bever, July 13, 2017 (“Bever Deposition”), pp. 135–136 (“Q. Okay. And do you have any basis to believe that data would have been incomplete? A. Yes. Q. And why is that? A. Because since I have moved to admissions and financial aid, I have a better understanding of admissions data. Q. And what in particular do you think you have an understanding of now that you didn’t know then? A. The process. Q. And what in particular—how in particular does that affect the reliability of the data that OIR would have used in 2013? A. We oversimplified the process. Q. And what do you mean by ‘oversimplified the process’? A. So in that analysis we just reviewed only four ratings were included. Q. And—and why does that oversimplify the process? A. There are many other

55. It is also worth noting that, outside of the Harvard data, there is evidence that the populations of Asian-American and White students applying to colleges differ from each other on non-academic factors. For example, as I noted in my first report, academic literature indicates that, on average, Asian-American high school students apply to selective universities at higher rates than students from other ethnic groups, even after controlling for whether or not a student is qualified on key academic dimensions.⁵⁰

56. This is important because an implicit assumption in Prof. Arcidiacono's argument that the personal rating is biased is that, absent bias by Harvard, there should be no average differences in personal ratings between White and Asian-American applicants to Harvard. However, given the underlying differences in application behavior to select universities between the two groups found in the academic literature, there is no reason to expect that Asian-American and White *applicants to Harvard* would possess the same qualifications and/or life experiences, on average, across the many dimensions Harvard evaluates—even if we assume that the two groups have the same average qualifications and/or life experiences in the population at large. Indeed, as detailed throughout this section, the differences we see across the key profile ratings are consistent with differences we see in the inputs into those ratings. Further, the fact that Prof. Arcidiacono selectively concludes that racial bias is the cause of *only one* of those average differences (the difference in personal ratings) establishes the unreliable and selective nature of his methodology.

57. Finally, even if we assumed—counter to the evidence—that the unexplained racial gaps in Prof. Arcidiacono's ratings regression reflect racial bias, the proper test for whether such alleged bias in the ratings led to bias in admissions decisions would be to estimate an admissions model where

factors we review in admissions.”), and p. 156 (“A. So again this does not reflect the process by which we do admissions. Q. And why doesn't it reflect that? A. Because we review many factors, some of which can be data and some of which are not.”). See also Deposition of Mark Hansen, July 19, 2017 (“Hansen Deposition”), pp. 195–196 (“Q. Are there other factors that you may not have thought of earlier today, that also might explain the apparent difference in likelihood of admission, based on one racial identification? [...] THE WITNESS: Yes. (BY MR. DULBERG): Q. The modelling that you undertook in Exhibit 4, does not take social economic status into account; correct? [...] THE WITNESS: That appears correct, yes. Q. There are other factors and data that are not reflected in these models; correct? [...] THE WITNESS: Certainly, yes.”).

⁵⁰ Card Report, p. 37, footnote 64 (“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.”).

Harvard’s actual (allegedly biased) ratings are replaced with the predicted ratings from Prof. Arcidiacono’s ratings regression, with the alleged “biases” that Prof. Arcidiacono measures netted out. In Exhibit 9, I present the results of such a model. Specifically, I use his ratings models (for the personal, academic, and extracurricular ratings) to predict “bias-free” personal, academic, and extracurricular ratings for each applicant and then include these ratings in my preferred model instead of the actual ratings assigned by Harvard admissions officers.⁵¹ As Exhibit 9 shows, using these ratings I continue to find no evidence of bias against Asian-American applicants. Although the overall estimated effect becomes slightly more negative, it is still far from statistically significant, and there is still a mix of positive and negative effects over the six classes.

Exhibit 9

There is no consistent or statistically significant evidence of bias against Asian-American applicants even adjusting for what Prof. Arcidiacono alleges as bias in the personal rating

Class	Average Marginal Effect of Asian-American Ethnicity (Not Statistically Significant)
1. 2014	-0.27
2. 2015	-0.18
3. 2016	-0.38
4. 2017	0.36
5. 2018	-0.46
6. 2019	0.29
Overall	-0.11

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 from updated Card model using adjusted academic, extracurricular, and personal ratings. Data are from applicants to the classes of 2014 – 2019 in Prof. Arcidiacono’s expanded sample including athletes. An applicant’s adjusted rating is the rating with the highest predicted probability according to Prof. Arcidiacono’s rating model excluding other profile ratings from the controls and turning off the effect of race. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

3.2. There is no basis for Prof. Arcidiacono’s decision to exclude parental occupation, intended career, or staff interviews

58. Beyond his decision to exclude the personal rating from his admissions models, Prof. Arcidiacono identifies several other variables that I included in my admissions model that he claims

⁵¹ Prof. Arcidiacono includes profile ratings as independent variables in his ratings regressions. For example, in his personal rating model, he includes the academic and extracurricular ratings as independent variables. For this analysis, I re-estimate his ratings models removing the profile ratings from the set of control variables since the purpose of this exercise is to ensure that the allegedly biased ratings are not impacting my estimate of the effect of Asian-American ethnicity.

should not be included: parental occupation, intended career, and staff interviews. As with the personal rating, including these variables reduces the alleged “bias” Prof. Arcidiacono finds in his regression model. This fact helps to explain why Prof. Arcidiacono reaches a different conclusion about the alleged bias against Asian-American applicants than I do.

59. In this sub-section, I summarize the evidence that definitively shows that all of these variables are important to Harvard’s admissions process, and that Harvard relies on the information they contain in deciding whom to admit. For these reasons, I conclude that there is no objective basis for their exclusion from the admissions model. As with the personal rating, Prof. Arcidiacono’s failure to consider inputs that are critical to Harvard’s decision-making process, without sufficient factual basis for doing so, results in a model that fails to accurately reflect the process being modeled.

3.2.1. Parental Occupation

60. Prof. Arcidiacono asserts that parental occupation should be excluded from a model of admissions for two reasons: it is allegedly not important to Harvard’s process, and it behaves in an allegedly unreliable manner over time.

61. In support of his first critique, Prof. Arcidiacono states that “there is no evidence in the records that Harvard’s admissions office considers parental occupation important aside from its value as a measure of [socioeconomic status].”⁵² This argument does not justify excluding important information from the model for at least two reasons.

62. First, as explained in detail in my first report, and summarized above in Section 3, the full context of each candidate’s life is essential to Harvard’s review process. Harvard seeks to admit candidates with a wide range of experiences and skills who can engage with and help educate classmates and faculty. Parental occupation is an important fact from which Harvard gleans information about family background and socioeconomic status. The importance of parental occupation in the admissions process is supported by numerous pieces of evidence in the record. For example:

⁵² Arcidiacono Rebuttal, p. 6.

- Parental occupation is one of the pieces of information reported on docket sheets used by admissions officers during committee meetings.⁵³
- Parental occupation is also reported on an applicant’s Summary Sheet (used by admissions officers to synthesize application information).⁵⁴ The summary sheet is viewed by admissions officers as containing key pieces of information that guide the discussion about a candidate.⁵⁵
- Deposition testimony from admissions officers confirms that they consider parental occupation a relevant piece of information in the admissions process.⁵⁶
- Additionally, Harvard’s Discussion Guide to its Casebook (which is used to train admissions officers) contains examples in which **Redacted**
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⁵³ Docket sheets, “P, R & S Dockets- Official #1 Class of 2018,” HARV00056250 – 57311 at HARV00057289; Deposition of William Fitzsimmons, August 3, 2017 (“Fitzsimmons Deposition”), pp. 254–255 (“...and then the entire application would go up on the screen. So all the parental information...everything we’ve discussed...”); Deposition of Marlyn Elizabeth McGrath, Volume I, June 18, 2015 (“McGrath Deposition 2015”), pp. 180–181 (“Q. And you said at the point that it goes to committee, a physical docket is prepared? A. A physical docket is prepared. Q. And what does that look like? A. It has...a list of the candidates from that school with certain salient information like test scores, grades, ... , parental occupation...”).

⁵⁴ See, for example, Summary sheet, HARV00076219 – 20.

⁵⁵ Deposition of Chris Looby, June 30, 2017 (“Looby Deposition”), pp. 30–31 (“Q. And what is a ‘summary sheet’? A. It’s a sheet that provides a summary of the application. Q. And how is a summary sheet used? ...A. Many ways. Q. Can you please list them? [...] A. Provides an overview for anyone who might view that application. Q. Any others? A. Could be used during the presentation of an application. Q. Any other ways? A. I believe they can be used for training purposes.”); McGrath Deposition 2015, pp. 96–97 (“There’s—there is a space on the electronic thing, and there’s a piece of paper in the paper version, where people, as they review, once the folder’s complete that I just described, once that’s complete and begun to be read, the people who read the folder, the readers make their comments on a sheet of paper, which then is available to the subsequent readers and to the full committee. Q. Is that sometimes referred to as a summary sheet? A. Yes. Q. And are comments from admissions officers or other people in your office always placed on the summary sheet either in the electronic or paper format, depending on timing? A. That’s the idea, yes.”)

⁵⁶ Fitzsimmons Deposition, p. 201 (“Q. How does Harvard determine whether or not an applicant is socioeconomically disadvantaged? A. ...We also have information at the outset about the parents’ educational and professional backgrounds.”); McGrath Deposition 2015, pp. 180–181 (“Q. And you said at the point that it goes to committee, a physical docket is prepared? A. A physical docket is prepared. Q. And what does that look like? A. It has...a list of the candidates from that school with certain salient information like test scores, grades, ... parental occupation...”); Looby Deposition, p. 59 (“Q. What types of information would you assess in trying to determine whether you should code an applicant as disadvantaged? ... A. Could be parent jobs.”).

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57

- Finally, beyond the record in this case, occupation is also one of the most informative measures of socioeconomic status relied upon in the economics and social sciences literature.⁵⁸

63. Second, even if one were convinced that parental occupation is used by Harvard only as an indicator of socioeconomic status (as Prof. Arcidiacono seems to be), it would still be inappropriate to exclude it from the model. Prof. Arcidiacono and I agree that Harvard considers socioeconomic status in its admissions process, and we both include multiple measures of socioeconomic status besides parental occupation (e.g., whether the applicant has been identified as “disadvantaged,” whether the applicant received a fee waiver, and whether the applicant applied for financial aid).⁵⁹ Prof. Arcidiacono’s decision to exclude just one of the available measures of socioeconomic status—a measure that is clearly considered in Harvard’s admissions process—is unwarranted and inconsistent with his own methodology of including multiple socioeconomic factors.

64. Moreover, relative to the other socioeconomic factors Prof. Arcidiacono includes in his model, parental occupation is a more detailed and more informative measure of socioeconomic status.

⁵⁷ Discussion Guide to the 2012 Casebook, HARV00018164 – 176 (“Casebook Discussion Guide”) at HARV00018167 – 8.

⁵⁸ See, for example, David Zimmerman, “Regression Towards Mediocrity in Economic Stature,” *The American Economic Review* 82(3), 1992, pp. 409–429; Otis Dudley Duncan, “A Socioeconomic Index for All Occupations,” in *Occupations and Social Status*, ed. Albert J. Reiss, Jr. (Free Press, 1961), pp. 109–138; Greg J. Duncan and Katherine A. Magnuson, “Off With Hollingshead: Socioeconomic Resources, Parenting, and Child Development,” in *Socioeconomic Status, Parenting, and Child Development*, ed. Marc H. Bornstein and Robert H. Bradley (Lawrence Erlbaum Associates, Inc., 2003), pp. 83–106.

⁵⁹ Other measures such as the College Board neighborhood median income variable are only proxies which may or may not accurately reflect an individual applicant’s circumstances.

For example, whether the applicant applied for financial aid provides only very limited information on an applicant's socioeconomic status because it is a simple binary indicator of "Yes" or "No." In fact, the vast majority of domestic applicants (76%) apply for financial aid.⁶⁰ The fee waiver variable and disadvantaged flag are also similarly limited measures of SES; like the financial aid variable both are simple "dummy" variables that delineate only a binary indicator of socioeconomic status—i.e., fee waiver versus no fee waiver. Parental occupation, by contrast, includes 24 categories.

65. One formal way to demonstrate that parental occupation contains more relevant information than the other three measures of socioeconomic status is to calculate how well each variable (on its own) explains admissions decisions for domestic applicants to Harvard using a simple regression. When I do this, I find that parental occupation explains more about admissions decisions than any of the other three individual-specific measures of socioeconomic status. Specifically, a model with just parental occupation has a Pseudo R-Squared of 0.011, while models with only fee waiver, only financial aid, and only disadvantaged have Pseudo R-Squared values of 0.0004, 0.0063, and 0.0023.⁶¹ In other words, without controlling for any other factors, parental occupation explains more than twenty times as much as fee waiver, nearly twice as much as financial aid, and almost five times as much as the disadvantaged flag. Finally, outside the record of this case, a substantial body of social science literature uses parental occupation as an indicator of socioeconomic status.⁶² Given all of these facts, there is simply no basis for Prof. Arcidiacono to exclude parental occupation from the admissions model, even if it were (as he views it) purely a measure of socioeconomic status.

66. Prof. Arcidiacono also claims that the parental occupation field in Harvard's admissions database should be excluded because it fluctuates "wildly" from year to year, a pattern that he claims proves it is unreliable.⁶³ There are two important reasons why this critique is wrong.

67. First, Prof. Arcidiacono overstates the severity of these allegedly "wild" fluctuations by focusing on a small number of occupation categories that exhibit changes over time. While it is true that some occupational categories do fluctuate in size over time, the majority of occupations—including the most common—behave in a stable fashion. Indeed, if one looks at the patterns across all occupations and all years (as shown in Prof. Arcidiacono's own tables B.3.1N and B.4.2N), it is clear that the changes Prof. Arcidiacono complains about are much less pronounced than he suggests.

⁶⁰ See workpaper.

⁶¹ See workpaper.

⁶² See, for example, David Zimmerman, "Regression Towards Mediocrity in Economic Stature," *The American Economic Review* 82(3), 1992, pp. 409–429; Otis Dudley Duncan, "A Socioeconomic Index for All Occupations," in *Occupations and Social Status*, ed. Albert J. Reiss, Jr. (Free Press, 1961), pp. 109–138; Greg J. Duncan and Katherine A. Magnuson, "Off With Hollingshead: Socioeconomic Resources, Parenting, and Child Development," in *Socioeconomic Status, Parenting, and Child Development*, ed. Marc H. Bornstein and Robert H. Bradley (Lawrence Erlbaum Associates, Inc., 2003), pp. 83–106.

⁶³ Arcidiacono Rebuttal, p. 6.

Furthermore, these fluctuations primarily reflect a change in how data about occupations were recorded in Harvard’s database starting in 2015. Harvard’s database indicates a switch from using one set of occupation codes in 2014, to using two sets in 2015, with the majority of applicants classified under the new system. As a result, certain occupational categories appear to “fluctuate” between 2014 and later years. For example, Prof. Arcidiacono notes that while about 1,000 parents per year were coded as self-employed in each year from 2015 to 2019, no parents were coded as self-employed in 2014; this is because Harvard’s database did not have a code for self-employed parents in 2014. Similarly, the “low skill” occupation appears to drop sharply in 2015; but this is simply because “low skill” was not an option under Harvard’s new, more prevalent coding. The data also suggest that Harvard stopped consistent use of the “unemployed” code starting with the class of 2018. Such recoding is a common issue in many data sets that are widely used in econometric research, such as the American Community Survey, Public Use files of the decennial censuses, and the Current Population Survey.⁶⁴

68. Most importantly, there is a simple solution to the problem Prof. Arcidiacono identifies—estimate the admissions model separately for each year of applicants, then pool the estimated racial effects from each year into a single summary measure. As explained in my original report, a key methodological advantage of estimating separate admissions models for each year is that it accounts for the fact that the overall composition of Harvard’s applicant pool changes substantially from year to year. In fact, I provided several examples of key variables whose distributions changed substantially over time, including intended concentration, docket, and early action. Such year-to-year compositional changes are not a problem at all so long as the admissions models are estimated separately for each year. Such an approach ensures that applicants who apply in a year where, say, there are an unusually large number of applicants whose parents are engineers are compared only to

⁶⁴ U.S. Census Bureau, “Industry and Occupation Code Lists & Crosswalks,” available at <https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html>, accessed March 8, 2018; U.S. Bureau of Labor Statistics, “Historical comparability of occupation and industry data from the Current Population Survey,” available at <https://www.bls.gov/cps/cpsoccind.htm>, accessed March 8, 2018; IPUMS USA, “ACS Occupation Codes,” available at <https://usa.ipums.org/usa/volii/c2ssoccup.shtml>, accessed February 19, 2018.

Indeed, Prof. Arcidiacono himself has used some of these datasets, and has also mapped occupational codes from university-specific data to ACS categorizations; see Peter Arcidiacono et al., “Recovering Ex Ante Returns and Preferences for Occupations Using Subjective Expectations Data,” NBER Working Paper #20626, October 2014, p. 9 (“We utilize data on wages, college major, and current occupation from the 2009-2011 ACS.... Majors in the ACS were categorized similarly to the Duke data. Several majors in the ACS are not offered at Duke; to the extent they clearly fell into one of the six major categories, they were included in that category. Occupations were constructed by matching the occupations categories in the ACS with the occupation groupings in the Duke data.”) and footnote 17 (“[s]cience, computing, and engineering occupations were coded as science and technology careers; medicine was coded as a health career; business and finance were coded as business careers; legal was coded as a law career; nonprofit occupations as well as local, state or federal occupations were coded as government/nonprofit”).

the other applicants who applied *within that same year* (where the pool has that same feature).⁶⁵

69. In fact, Prof. Arcidiacono acknowledges—and partially implements—this solution in his own analysis. Specifically, after I pointed out in my first report that variables like intended concentration, docket, and early action behaved differently across years, Prof. Arcidiacono changed his admissions model to allow those variables to have different effects in different years. In other words, for some categorical variables with categories that change over time, Prof. Arcidiacono chose to employ a standard methodological solution that allowed him to retain those variables (rather than exclude them from the model, as he advocates for parental occupation).⁶⁶ Prof. Arcidiacono’s inconsistent application of this approach, and his insistence on leaving out parental occupation, is noteworthy because parental occupation is a variable that reduces the alleged “bias” against Asian-American applicants found in Prof. Arcidiacono’s model (as I show in Section 4 below).

70. Perhaps the most striking example of Prof. Arcidiacono selectively applying which variables to include or not based on their volatility over time is the disadvantaged flag. As noted above, Prof. Arcidiacono views this flag as a critical indicator of socioeconomic status, and relies heavily on this variable for his opinions. Yet, like parental occupation, the coding of the disadvantaged flag varies substantially over time. For example, the share of applications flagged as disadvantaged nearly doubles in 2019 relative to years prior (in 2018 it is 9.9% and in 2019 it is 17.8%).⁶⁷ Such a large unexplained change is the exact reason Prof. Arcidiacono cites for excluding parental occupation from his model.⁶⁸ It is telling that when choosing between two variables that exhibit similar volatility, Prof. Arcidiacono chose to include the factor that leads to an estimated effect of Asian-American ethnicity that is more negative (disadvantaged) and to exclude the factor that leads to a less negative effect (parental occupation).⁶⁹

71. An alternative approach, commonly used to address concerns that certain categories of a variable like parental occupation change over time in an unreliable manner, is to include the volatile categories (e.g., “Unemployed”) in a combined “missing and unstable” category across all years, and leave the other more stable categories (e.g. “Lawyers, Judges”) in the model. This solution allows the model to use the parental occupation information that Prof. Arcidiacono believes is reliable, rather

⁶⁵ In Appendix B.1 I address a more technical criticism from Prof. Arcidiacono about how I aggregated the available occupational categories to create the indicator variables in my regression. I show that the findings of my main regression models are robust to a variety of reasonable ways of constructing occupation categories.

⁶⁶ Arcidiacono Rebuttal, pp. 69–70.

⁶⁷ See workpaper.

⁶⁸ Arcidiacono Rebuttal, pp. 31–33. (“These inconsistencies raise doubts about the reliability of the field and its usefulness as a control. If there is little reason to trust the accuracy of a factor, incorporating it into a model will not inform the resulting estimates. Prof. Card nowhere offers an explanation for why these data would vary so wildly across these years.”)

⁶⁹ See workpaper.

than throw out parental occupation information entirely. Prof. Arcidiacono does not explore this alternative approach. As I will discuss in Section 4, in order to be certain that the issues Prof. Arcidiacono raises do not affect the final conclusions of my results, I have also estimated my preferred model making this modification (despite the fact that my year-by-year model already addresses this issue) and show that it leads to the same conclusions.

3.2.2. *Intended Career*

72. Prof. Arcidiacono also argues that data on applicants' intended careers should be excluded from a model of admissions. As I noted in my first report, intended career is another piece of information Harvard relies on to better understand an applicant's life experience and interests. This should not be surprising. A student body in which all students had the same career interests, or the same intellectual interests, would have less diversity of thought. I included intended career in my admissions model both because the record indicates it can meaningfully influence an applicant's chance of admission, and because it exhibits differences between ethnic groups. Specifically, I noted:

[A]n 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. For example, the Casebook Discussion Guide notes the following about one candidate:
Redacted

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73. It is worth noting that a recent study that analyzed how undergraduates at Harvard and Stanford gain information about different careers, and make different career choices when they leave college, found that (a) 30% of White students in the sample were interested in "impact careers" (defined as education, public service, nonprofits, and philanthropy, and "creative-class" careers, such as academia and journalism), as compared to 15% of Asian-American students, and (b) 56% of Asian-American students in the sample were interested in Consulting or Finance, as compared to 41% of White students.⁷¹

⁷⁰ Card Report, p. 44.

⁷¹ Amy J. Binder, Daniel B. Davis, and Nick Bloom, "Career Funneling: How Elite Students Learn to Define and Desire 'Prestigious' Jobs," *Sociology of Education* 89(1), 2016, pp. 20–39 at pp. 24–25.

74. Despite the clear importance of intended career in the admissions process, and the fact that preferences for intended career differ on average between ethnic groups, Prof. Arcidiacono excludes the variable from his model. He claims, as he did for parental occupation, that intended career “varies in highly unusual and unexplained ways over time, undermining its reliability as a variable and its usefulness as a control.”⁷² As noted above, however, one of the main purposes of estimating the admissions model separately for each admissions class is to solve this exact problem. As I detailed in my original report, the exact composition of each admissions class changes from year to year on any number of dimensions. These types of year-to-year compositional changes, however, do not pose any methodological problems for the admissions model because the admissions model is focused on comparing applicants within the same year.

75. Prof. Arcidiacono also overstates the changes that occur over time in the intended career variable. Prof. Arcidiacono’s Table 7.1N shows how the intended career variable changes over time for all categories.⁷³ As is clear, the biggest change occurs in 2018; outside of 2018 the values across all of the categories are generally stable. As with parental occupation, Prof. Arcidiacono’s omission of intended career is not defensible. A more reliable solution would be to simply allow the variable to have different effects in different years, as he does with other variables that change substantially over time, and as I do below in Section 4 with my year-by-year model.

3.2.3. Staff Interviews

76. Prof. Arcidiacono also excludes staff interviews from the admissions model. As with intended career, Prof. Arcidiacono does not dispute the importance of staff interviews to the admissions process. Instead he argues that the variable should be excluded because he understands that staff interviews are given to only a small portion of the applicant pool and are less likely to be given to Asian-American applicants, and because people receiving staff interviews have a good chance to be admitted.⁷⁴

77. The fact that only a small number of applicants participate in staff interviews is not a sufficient basis to exclude staff interview ratings from the model. Given the competitive nature of the process, and the many dimensions over which Harvard tries to distinguish between so many strong applicants, additional information (like the staff interview) helps improve the model.

78. That said, to address the concerns Prof. Arcidiacono raises, in Section 4, I test whether the exclusion of the staff interview in my model in any way changes the overall conclusions from my key

⁷² Arcidiacono Rebuttal, p. 62.

⁷³ Arcidiacono Rebuttal, p. 63.

⁷⁴ Arcidiacono Rebuttal, pp. 66–67.

findings. As I show there, it does not. Whether or not we include it in the model does not significantly change the effect associated with Asian-American ethnicity.

3.3. Prof. Arcidiacono’s use of a pooled model is inconsistent with an essential feature of Harvard’s admissions process and thus has no methodological basis

79. In Section 5.3 of my original report, I explained why it is critical to analyze Harvard’s admissions decisions separately by year. In his rebuttal, Prof. Arcidiacono challenges that approach for two reasons. First, he claims that I am incorrect in asserting “all applicants each year are compared to all other applicants.”⁷⁵ Second, he asserts that estimating models separately by year “reduces the statistical power of the sample.”⁷⁶ Prof. Arcidiacono’s claims lack any factual support and are entirely without merit.

80. First and foremost, Harvard’s admissions process is, in fact, a year-by-year process. Applicants from the class of 2019 are not compared to applicants from the class of 2017, and any analysis that assumes they are is inherently flawed. Prof. Arcidiacono’s response that it is “wrong that all applicants each year are compared to all other applicants”⁷⁷ (which I will turn to in the next section of this report) completely misses this point. What is relevant is not whether every candidate *within a year* is compared to every other candidate in that year, but whether applicants *in different years* are compared to each other. Again, it is nonsensical to assume that an applicant for the class of 2019 is competing with an applicant for the class of 2017, yet that is the assumption Prof. Arcidiacono imposes in his own model. On this critical issue, Prof. Arcidiacono offers no rebuttal.

81. The second reason Prof. Arcidiacono offers for pooling applicants from different years into a single model is that estimating a separate model for each year “reduces the statistical power of the sample.”⁷⁸ Prof. Arcidiacono offers a hypothetical example of discrimination against women in promotions at a law firm over a six-year period, and asserts that in that hypothetical example performing the analysis year-by-year would “reduce the statistical significance of findings of discrimination, but it would not make any sense.”⁷⁹ First, it is worth noting that the example of promotion to partner at a law firm is fundamentally different from admissions to Harvard because,

⁷⁵ Arcidiacono Rebuttal, p. 34.

⁷⁶ Arcidiacono Rebuttal, p. 34.

⁷⁷ Arcidiacono Rebuttal, p. 34.

⁷⁸ Arcidiacono Rebuttal, p. 34.

⁷⁹ Arcidiacono Rebuttal, p. 35.

among many other things, candidates not promoted at a law firm in a given year could be (and typically are) considered again for promotion in future years. Second, as I explained in my first report, I resolve the purported problem of reduced statistical significance by taking the average of the estimated race effects (e.g. the effect of Asian-American ethnicity) from the models for each year of data, which is a standard statistical approach to this issue.⁸⁰ In other words, Prof. Arcidiacono's hypothetical is thoroughly misleading. He ignores the important fact that after doing the analysis by year, I average the results across years to ensure statistical power.

82. In fact, it is possible to directly compare how precisely the effect of Asian-American ethnicity can be estimated (i.e. the standard error) by Prof. Arcidiacono's pooled model versus my year-by-year model, in which the six yearly estimates are averaged into a single effect representing the average effect over the six classes of applicants. As we can see in Exhibit 10, the precision of the two approaches is nearly identical. Specifically, in the first two panels of this exhibit, I estimate Prof. Arcidiacono's model pooled and then also separately year-by-year. The appropriate measure of precision for each model is the standard error. As a general matter standard errors decrease (and precision increases) when a model has more data. What we see is that the standard error from the pooled model and the year-by-year model averaged across years is nearly identical at 0.15.⁸¹ The reason for this is simple: by averaging the estimates across years, I am taking advantage of the same number of observations as Prof. Arcidiacono does by pooling them.⁸² Prof. Arcidiacono's assertion that there is a reduction in statistical power from fitting year-by-year models is obviously not correct. Moreover, the results in the second and third panels of Exhibit 10 demonstrate that the standard error of the average effect from my year-by-year model is actually smaller than that of Prof. Arcidiacono's pooled model (0.14 vs. 0.15). This is because my year-by-year model does a better job of explaining admissions decisions. Thus, contrary to Prof. Arcidiacono's assertion, my model, fit year-by-year and then averaged, has greater precision (i.e., greater statistical power) in estimating the effect of Asian-

⁸⁰ Card Report, p. 67, footnote 116 ("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.").

⁸¹ The standard error for the weighted average of the yearly effects is computed according to the following formula:

$$s.e._{average} = \sqrt{\sum_{i=2014}^{2019} \left[s.e._i * \left(\frac{N_i}{N_{Total}} \right) \right]^2}$$

⁸² Technically, while Prof. Arcidiacono and I both take advantage of the same number of observations, there is an additional trade-off which affects the precision of the estimates. This relates to which method has more "degrees of freedom" and which method has a better fit. The degrees of freedom refer to the total number of observations in the sample minus the total number of parameters being estimated. My method of averaging the estimates from the 6 yearly models utilizes the same number of observations as Prof. Arcidiacono's but has more parameters because I estimate a separate model for each year. This means that my estimate has fewer degrees of freedom relative to Prof. Arcidiacono's. But, because my year-by-year models fit the data better, on balance, the precision of my estimates is slightly higher.

American ethnicity on admissions than his pooled model.

Exhibit 10

Estimating a model either pooled or year-by-year will produce extremely similar measures of statistical precision

Class	Standard Error	Number of Asian-American Applicants	Total Number of Applicants
<u>Arcidiacono Model, Estimated by Year</u>			
1. 2014	0.42	6,036	21,238
2. 2015	0.37	6,991	24,845
3. 2016	0.40	6,305	23,906
4. 2017	0.37	6,255	23,949
5. 2018	0.36	6,931	23,987
6. 2019	0.35	6,935	25,228
Overall	0.15	39,453	143,153
<u>Arcidiacono Model, Pooled</u>			
7. 2014 – 2019	0.15	39,453	143,153
<u>Card Year-by-Year Model</u>			
8. Overall	0.14	39,408	142,838

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

Note: Models are estimated on Prof. Arcidiacono’s expanded sample including athletes. The first panel shows standard errors for Prof. Arcidiacono’s model estimated year-by-year. The overall standard error (0.15) is the standard error for the weighted average of the yearly effects. The second panel shows the standard error for Prof. Arcidiacono’s pooled model. The third panel shows the overall standard error for the weighted average of the yearly effects as estimated from the Card model.

83. Before moving on, it is worth noting that, in my first report, I identified another important reason for estimating the model separately for each year—the pooled model imposes the assumption that Harvard places the same value on each characteristic across all years. In my first report, I explained this problem as follows:

Second, a closely related problem with the 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 of relevant factors can also change, which can cause the value Harvard places on any given factor to also change from year to year.⁸³

84. As noted above, Prof. Arcidiacono's rebuttal has partially acknowledged the importance of this methodological concern. Specifically, for some of the key variables that he chose not to exclude from his model, Prof. Arcidiacono has added interaction terms between those variables and the year variables. However, his decision to selectively interact only some of his variables across years, rather than estimate separate models for each year, is a less neutral approach than my approach of estimating each model separately by year, because it involves more subjective judgment. Not surprisingly, perhaps, given the patterns associated with his other modeling choices, Prof. Arcidiacono's decision to not estimate his models separately by year has the effect of increasing the alleged disparity between Asian-American and White applicants.

3.4. Prof. Arcidiacono's decision to exclude certain types of applicants from his model is inconsistent with how Harvard's admissions process works, and is methodologically unsound

85. In both of his reports, Prof. Arcidiacono performs all of his key analyses on a restricted sample of applicants that he calls his baseline sample. This sample excludes recruited athletes, lineage applicants, those on the Dean's or Director's interest lists, and children of a member of Harvard's faculty and staff—applicants I refer to as ALDC applicants (Athlete, Lineage, Dean/Director list, Children of faculty and staff) for brevity. In addition, in his initial report, he excluded early admission applicants from his baseline sample.⁸⁴ My first report criticized his use of the baseline sample; in his rebuttal, Prof. Arcidiacono continues to defend his use of the baseline sample.

86. Prof. Arcidiacono offers two main justifications for his use of the baseline sample. First, he argues that the candidates he excludes from the baseline sample are “subject to special admissions procedures[,]” i.e., their admission process is distinct from that of other applicants.⁸⁵ Second, in his rebuttal, he offers the new argument that the purportedly different admissions process for ALDC candidates is not affected by the alleged discrimination, and thus inclusion of such applicants in an empirical analysis will “obscure the penalty Harvard imposes on Asian-American applicants.”⁸⁶ In this section, I explain why neither of the reasons offered by Prof. Arcidiacono is based on available facts in the record or is a methodologically sound reason for excluding these candidates from the

⁸³ Card Report, pp. 51–52.

⁸⁴ In his first report Prof. Arcidiacono excluded early action applicants from his baseline sample, but in his rebuttal he includes them. Arcidiacono Rebuttal, p. 69.

⁸⁵ Arcidiacono Rebuttal, p. 69.

⁸⁶ Arcidiacono Rebuttal, pp. 19, 69.

analysis.

3.4.1. Prof. Arcidiacono's claim that ALDC candidates are part of a "special" admissions process, and, thus, do not compete with other candidates is not supported by the data, documents, or depositions

87. In my first report, I argued that Prof. Arcidiacono's baseline sample was flawed because it was inconsistent with how Harvard's actual admissions process worked. I am aware of no evidence in the record that Harvard conducts a different admissions process for certain types of candidates whereby those candidates do not compete against candidates from the broader pool. Certainly, Prof. Arcidiacono has not presented any such evidence. As explained in my first report:

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.⁸⁷

88. Prof. Arcidiacono responds by continuing to insinuate that ALDC candidates are part of a different process⁸⁸—yet his rebuttal still offers no evidence to support that assertion.⁸⁹ As I explain

⁸⁷ Card Report, p. 57. In my initial report, I made two additional points. First, I noted that excluding early admission applicants was particularly problematic because (a) early admission applicants who are not admitted early remain in the regular pool of applicants, and (b) early admission did not exist for the classes of 2014 and 2015, which means that excluding early admission applicants has a differential effect on the sample in those two years. Second, I noted that throwing out these data reduced the precision of his statistical model (Card Report, pp. 57–58).

⁸⁸ Arcidiacono Rebuttal, pp. 34, 69; Arcidiacono Rebuttal, Appendix A, p. 3.

⁸⁹ If anything, the evidence suggests the opposite. See, for example, an email chain in which the women's hockey coach asks for feedback from admissions officers on a draft email she plans to send to Dean Fitzsimmons in advance of admissions committee deliberations, in which she advocates for the admission of her recruits. Stone writes: "I am compelled to reach out about the importance of next week's admissions meeting for our hockey program. I am fully aware that there are many qualified applicants for next year's class; and I feel strongly that these **Redacted** are

below, exclusion of this large and relatively well-qualified group of applicants from the admissions model removes important information about how Harvard balances the many characteristics it considers in its decision process, and, thus, makes the model less reliable. Given the lack of any evidence of a separate process for ALDC candidates, and the importance of including a large and diverse sample in the model to allow accurate estimation of the tradeoffs between different characteristics in the review process, excluding ALDC applicants from the model is not methodologically defensible.

89. To better understand why excluding these ALDC candidates from the admissions model reduces the reliability of the model, it is helpful to consider the example of a candidate with an academic rating of 1 who is not an ALDC candidate. As I showed in my first report, applicants with an academic rating of 1 (and no other profile ratings of 1) have a 68% chance of admission.⁹⁰ That is more than ten times the average admission rate. Yet, while an academic rating of 1 certainly elevates a candidate's chances of admission, Harvard still evaluates all other dimensions of such a candidate's profile, which may entail comparing her to other candidates who perhaps have lower academic credentials, but who display more well-rounded excellence on multiple dimensions. Prof. Arcidiacono apparently agrees with this logic because he *does not* exclude candidates with an academic rating of 1 from his model.

90. The same logic holds for Prof. Arcidiacono's ALDC applicants. While it is certainly true that Harvard gives a "tip" to competitive candidates in certain categories, that "tip" by no means assures admission; nor does it remove the need for strength on other dimensions. A "tip" is just one part of an applicant's candidacy, and her remaining characteristics are considered in light of the many other highly qualified candidates in the applicant pool. By removing ALDC applicants from the admissions model, Prof. Arcidiacono's model is less reliable because it is not able to use the information from those applicants' other characteristics to help identify the tradeoffs that Harvard makes across candidates when deciding whom to admit.

91. The data bear this out. Specifically, if we look at the admissions data for the ALDC candidates that Prof. Arcidiacono excludes from his baseline sample, it is evident that many ALDC candidates have a high chance of admission, with or without the "tip" they receive for belonging to one of the ALDC categories. For example, one way to see the strength of ALDC applicants relative to the broader applicant pool is to compare the predicted probability of admission (according to my

no exception. I recognize their testing may not be that of others, yet what they will bring to the Harvard classroom, athletic area and community is immeasurable" (Email from Katey Stone to Grace Cheng and Nathan Fry, "FW: Harvard Women's Ice Hockey," November 30, 2012, HARV00022645). See also Harvard College, "Frequently Asked Questions," available at <https://college.harvard.edu/frequently-asked-questions>, accessed February 2, 2018 (Question: "Is there a separate admissions process for prospective athletes?" Answer: "No. We encourage students with athletic talent to contact our Athletic Department for information about any of Harvard's 42 varsity athletic teams.").

⁹⁰ Card Report, p. 28, Exhibit 4.

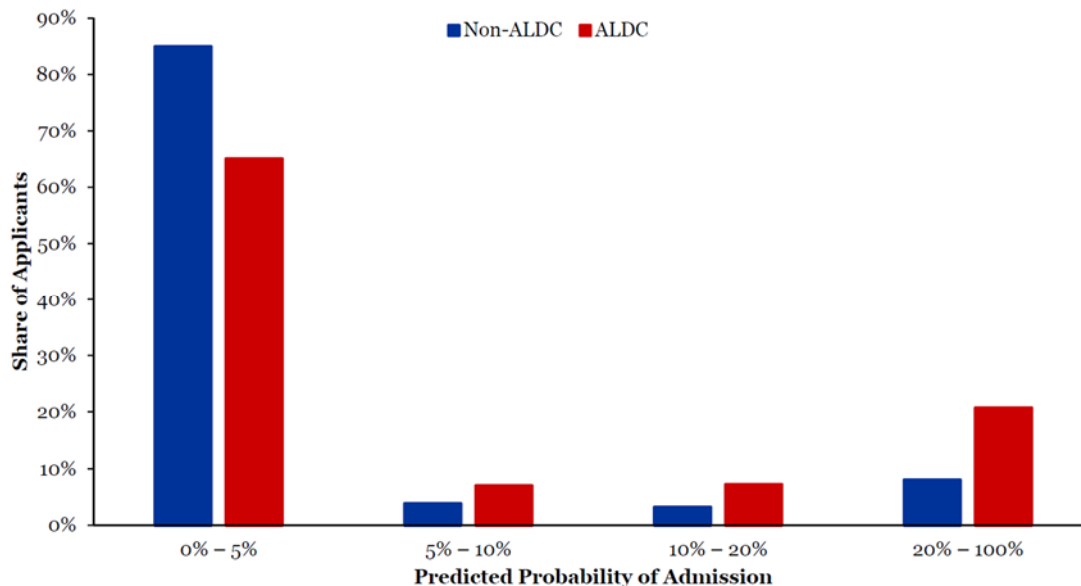
model) for ALDC applicants to that of non-ALDC applicants. Exhibit 11 shows predicted probabilities for both ALDC and non-ALDC applicants. In this exhibit, the predicted probabilities for ALDC applicants are calculated after turning off the “tip” associated with their ALDC status, and the results clearly show that ALDC applicants are stronger applicants even without the “tip” they receive for their ALDC status. Specifically, there are far more non-ALDC applicants with very low predicted probabilities of admission (i.e., predicted probabilities between 0% and 5%) and far more ALDC applicants with more competitive predicted probabilities. 21% of ALDC applicants have predicted probabilities of admission that are higher than 20%, compared to only 8% of non-ALDC applicants.

92. It is also the case that, among ALDC candidates who apply to Harvard, the candidates who are admitted are much stronger than the ones who are denied admission. Specifically, ALDC applicants who are admitted have an average predicted probability of admission that is 61 percentage points higher than that of ALDC applicants who are denied admission.⁹¹ In other words, ALDC applicants exhibit numerous traits other than their ALDC status that matter in determining whether they are admitted to Harvard, and it is their strength across multiple dimensions that is central to whether they are ultimately admitted. These facts imply that the ALDC sample provides important information to the admissions model that helps the model more reliably estimate the effect of those traits in the admissions process.

⁹¹ See workpaper.

Exhibit 11

ALDC applicants have higher predicted probabilities of admission than non-ALDC applicants, even without their ALDC “tip”



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 expanded sample including athletes. ALDC applicants’ predicted probability of admission is calculated removing the effect of being an ALDC applicant (i.e. removing the effect of being a recruited athlete, on the Dean’s or Director’s list, a lineage applicant, or a child of Harvard faculty and staff).

3.4.2. Prof. Arcidiacono’s claim that ALDC candidates should be excluded because there is no disparity in admissions decisions for such candidates is methodologically unsound

93. As noted, Prof. Arcidiacono’s rebuttal introduces a new and different argument about why the ALDC applicants must be removed from his baseline sample. Prof. Arcidiacono now claims that ALDC applicants are part of a separate process that does not discriminate, and thus any analysis of discrimination that includes them operates to “obscure” discrimination where it allegedly does occur.⁹² As I explain below, this argument is factually unsupported, methodologically flawed, and highly problematic.

94. The first and most important flaw in this approach is that ALDC applicants are not, in fact, considered in a separate admissions process. All Harvard applicants are reviewed in the same admissions process.

⁹² Arcidiacono Rebuttal, pp. 19, 34.

95. Second, Prof. Arcidiacono's claim that only a subgroup of applicants is subject to the alleged bias appears to be a form of data mining, a process whereby the researcher selectively chooses a subsample of the data to obtain a desired result. To help understand what this is, and why it is so problematic, consider a scenario in which it is undisputed that Harvard does *not* discriminate. Even in this scenario, it will be true, purely by chance, that some subgroups of Harvard's data will exhibit statistically significant unexplained disparities between racial groups due to a baseline level of unobserved differences in characteristics not in the model. Because there is no discrimination, these disparities will run in both directions—i.e., some subgroups of the data will show an unexplained gap in favor Asian-American applicants and some will show an unexplained gap in favor White applicants.

96. Given this reality, if one employs Prof. Arcidiacono's approach of excluding subgroups of the data where there is no evidence of a statistical disparity, then one is stacking the deck in favor of finding bias in the remaining data. This does not mean that there *is* discrimination in those remaining subgroups—it means only that the researcher has selectively analyzed the data to find a favorable result. That is why, as a general matter, the most reliable methodological approach for testing for a significant disparity in admission rates across race is to include *all* data points, and then to test whether there is a systematic disparity.

97. An exception to this approach can be made if there is clear evidence *outside of the data* that whatever alleged discriminatory behavior being analyzed is indeed limited to a subset of the data. In such a case, it might be appropriate to limit the sample. But Prof. Arcidiacono provides no external evidence that the alleged discrimination asserted by SFFA is not relevant for ALDC candidates. Nor is there any logical reason to assume it is not. If Harvard were in fact biased against Asian-American applicants, why would it not impose its supposed discriminatory preferences against legacies, or children of faculty, or athletes? What would be its motivation for selectively imposing such racial preferences? Prof. Arcidiacono's decision to exclude ALDC candidates appears to be based solely on the fact that the data show no negative effect of Asian-American ethnicity for this particular set of applicants. It is, thus, neither an appropriate nor an objective approach to building a model directed at analyzing the effect of Asian-American ethnicity on admissions decisions.

98. In fact, examining the effect of Asian-American ethnicity for the applicants Prof. Arcidiacono excluded suggests why he excluded them. Many ALDC applicants have an estimated effect of Asian-American ethnicity that is *positive*. For example, the estimated effect of Asian-American ethnicity among lineage applicants is 3.12 percentage points. This means that among lineage applicants, Asian-American applicants are admitted at a rate that is roughly three percentage points *higher* than the rate at which the model would expect White applicants with identical characteristics to be admitted. Similarly, the estimated effect of Asian-American ethnicity for

applicants who are on the Dean's or Director's interest lists or who are children of Harvard faculty and staff is positive.⁹³ Of course, these estimated positive effects do not mean that Harvard is biased in favor of Asian-American applicants in the specified categories. Instead, these positive effects show that there may be unobserved characteristics that vary both with race and with membership in the specified categories, and that affect applicants' likelihood of admission. That is a central reason why it is inappropriate to exclude the specified categories from the model, as Prof. Arcidiacono does.

99. Before moving on, it is worth noting that Prof. Arcidiacono does acknowledge that an alternative to excluding the data of ALDC applicants entirely is to include their data, and then add interaction terms between the race variables and the relevant dummy variables for the ALDC categories at issue (recruited athletes, lineage applicants, etc.). Prof. Arcidiacono asserts that such an approach is an alternative way to address his concern that such candidates should not be included in the model because they are not discriminated against.⁹⁴ In Section 4, I estimate a sensitivity analysis that employs this methodology. I continue to find no evidence of bias even with this approach.

⁹³ See workpaper.

⁹⁴ Arcidiacono Rebuttal, p. 36.

4. AN ADMISSIONS MODEL THAT INCLUDES RELEVANT INFORMATION FINDS NO EVIDENCE OF BIAS AGAINST ASIAN-AMERICAN APPLICANTS

100. In Section 3 above, I offered an explanation of the key methodological differences between Prof. Arcidiacono's approach and mine. In general, the differences in our approaches reflect differences in our modeling of how Harvard's admissions process works. As I explained above, given Harvard's clear philosophy of identifying "distinguishing excellences" across a wide variety of dimensions and evaluating each application within the context of the applicant's life experiences and opportunities, the most reliable model of Harvard's admissions process should include as much relevant information as possible about such distinguishing excellences and context factors. This is the approach I take. Prof. Arcidiacono, on the other hand, seeks to exclude several highly relevant pieces of information from the model, under the claim that they are either unreliable or biased (or both).

101. In this section, I present results from my admissions model. As I show below, when all relevant observable information is included, I find no evidence of bias against Asian-American applicants. Further, even when I perform a variety of sensitivity checks on my model to accommodate specific points raised by Prof. Arcidiacono, I continue to find no evidence of bias. Additionally, I show that for large subgroups of applicants (specifically, female applicants and applicants from California), there is evidence of a *positive* (though statistically insignificant) estimated effect of Asian-American ethnicity, suggesting that the negative effect of Asian-American ethnicity that Prof. Arcidiacono attributes to bias actually reflects unobserved differences between applicants, not bias. Finally, I show that Prof. Arcidiacono's argument that Harvard discriminates against all applicants on dockets where Asian-American applicants are more common is severely flawed—both conceptually and in its empirical implementation.

4.1. My preferred regression model shows no evidence of bias against Asian-American applicants

102. For the reasons detailed above in Section 3, the year-by-year admissions model I presented in my initial report remains my preferred model with one small change. For ease of comparing our results, I have adopted Prof. Arcidiacono's revised method of modeling the various ratings variables (i.e. the profile ratings, schools support ratings, and alumni interview ratings).⁹⁵ Implementing the modifications suggested by Prof. Arcidiacono (such as removing parental occupation and other key variables that capture information considered by admissions officers, estimating the model pooled across all years, or excluding ALDC applicants from the estimation

⁹⁵ In his rebuttal, Prof. Arcidiacono updated his ratings variables to account for the possibility that specific combinations of ratings can have different effects (by using interaction terms for certain combinations of ratings), as I had done in my initial report. Thus, for ease of comparison I use his approach in this report. A comparison of my initial report results with my results in this report demonstrates that the findings of my model are qualitatively the same with his approach versus my original approach. Card Report, p. 68, Exhibit 19.

sample) leads to a model that less accurately reflects the actual process, and is, therefore, less reliable. Therefore, I do not adopt these suggestions. See Appendix C for a full list of the variables in my updated model.

103. As shown in Exhibit 12, using my preferred admissions model, I continue to find no evidence of bias against Asian-American applicants. The average effect of Asian-American ethnicity is statistically insignificant, both overall and in each of the six years. The effect is slightly positive in three of the six years and slightly negative in three, with an overall effect (-0.05 percentage points) that—as with the effects for each individual admission class—is statistically indistinguishable from zero.

Exhibit 12

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 (Not Statistically Significant)
1. 2014	-0.39
2. 2015	-0.05
3. 2016	0.09
4. 2017	0.11
5. 2018	-0.42
6. 2019	0.34
Overall	-0.05

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 expanded sample including athletes. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

104. To illustrate the key differences between Prof. Arcidiacono’s updated preferred model and my preferred model and how these differences impact the estimated effect of Asian-American ethnicity, in Exhibit 13 I modify Prof. Arcidiacono’s model step by step until it matches mine. This approach shows how each incremental methodological change to the model changes the estimated effect of Asian-American ethnicity. The systematic pattern in Exhibit 13—whereby changes from Prof. Arcidiacono’s model lead to a smaller (less negative) estimated effect of Asian-American ethnicity in the admissions process—shows that many of Prof. Arcidiacono’s modeling choices appear to have been driven by the fact that they increase the alleged bias against Asian-American applicants (i.e., result in an estimated effect that is more negative), rather than by any objective evaluation of how Harvard’s admissions process actually works.

105. For example, a model that makes no changes to his model other than adding ALDC applicants back into the sample reduces Prof. Arcidiacono’s estimate of the negative effect of Asian-American ethnicity by 20%. Similarly, adding the personal rating, parental occupation information, intended career information, and staff interview ratings also significantly reduces his estimated effect. A model that includes ALDC applicants in addition to this information (and that is estimated year-by-year) eliminates 92% of Prof. Arcidiacono’s estimated effect, resulting in an effect that is not statistically distinguishable from zero.

Exhibit 13

Prof. Arcidiacono’s modeling decisions overstate the effect of Asian-American ethnicity on admissions

Model	Average Marginal Effect of Asian-American Ethnicity [1]
1. Prof. Arcidiacono's preferred model, excluding ALDC applicants [2]	-1.02 *
2. Add ALDC applicants	-0.81 *
3. Run year-by-year, add controls available in some years only [3]	-0.79 *
4. Add personal rating	-0.38 *
5. Add parental occupation controls	-0.19
6. Add intended career and staff rating indicator	-0.08
7. Remove interaction between disadvantaged and race	0.02
8. Remove interactions other than disadvantaged and race [4]	-0.05
9. Add perfect predictions to average marginal effect calculation	-0.05

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

Note: [1] Data are from Prof. Arcidiacono’s sample. Marginal effects are calculated relative to White applicants. * indicates significance at the 5% level. Marginal effects are reported as percentage point values. [2] ALDC applicants include lineage applicants, children of Harvard faculty and staff, recruited athletes, and applicants on the Dean or Director’s interest lists. Such applicants are added to the sample and indicators for ALDC groups are added to the model. [3] Additional controls include measures of participation in extracurricular activities and indicators for being born in the United States and having lived outside of the United States. [4] Includes interactions of female with intended concentration and race, interactions of race with indicator for Early Action, and interactions of race with missing SAT 2 average, missing alumni rating, and indicator for having a converted GPA of 35.

106. An important pattern in Exhibit 13 is that once the key changes I discuss in Section 3 are made to the model (i.e., the model is estimated by year, ALDC candidates are added back in, and information on the personal rating, parental occupation, intended career, and staff interview are included (row 6 onward)), the alleged bias is close to zero and statistically insignificant. While I believe that all of these changes to the model are necessary for it to be a reliable representation of the admissions process, I have also considered whether, starting with my updated model, any of my key findings are sensitive to the remaining methodological changes Prof. Arcidiacono argues I should implement. I walk through each of these in turn below.

107. First, Prof. Arcidiacono states that it is acceptable to include ALDC applicants in my

model as long as I interact the relevant variables (recruited athlete indicator, lineage applicant indicator, etc.) with the race variables. Specifically, he says: “It is thus essential to either (1) remove these [ALDC] applicants from the analysis; or (2) allow for the possibility that the effect of race is different for these applicants (i.e., interacting these variables with race).”⁹⁶ I have done as he suggests and estimated my updated model by allowing the effect of an applicant’s ALDC status to vary by race (i.e. included interactions of ALDC status with race) and I find that my results are not sensitive to this change. The average effect over the six years is unchanged. (See Exhibit 14.)⁹⁷

Exhibit 14

There is no consistent or statistically significant evidence of bias against Asian-American applicants even when the effect of ALDC status is allowed to vary by race

Class	Average Marginal Effect of Asian-American Ethnicity (Not Statistically Significant)
1. 2014	-0.29
2. 2015	-0.06
3. 2016	0.09
4. 2017	0.01
5. 2018	-0.44
6. 2019	0.36
Overall	-0.05

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

Note: Table shows average marginal effect of race on admission for Asian-American applicants relative to White applicants using the updated Card model with interactions of race and indicators for ALDC groups. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

108. Second, Prof. Arcidiacono argues that I “[err] in failing to include interaction terms.”⁹⁸ Specifically, he is concerned that my model does not allow the effect of disadvantaged status to vary

⁹⁶ Arcidiacono Rebuttal, p. 36.

⁹⁷ When Prof. Arcidiacono estimates his model that employs this approach and includes lineage applicants, children of Harvard faculty and staff, and applicants on the Dean’s or Director’s interest lists, he continues to exclude recruited athletes from the sample. As noted above, it is my understanding that recruited athletes are part of the same admissions process as all other applicants. I therefore include recruited athletes in my preferred model. However, because Prof. Arcidiacono presents a model that excludes recruited athletes, I also estimate my model excluding these applicants and confirm that it does not affect my finding that there is no evidence of bias against Asian-American applicants. See workpaper.

⁹⁸ Arcidiacono Rebuttal, p. 19.

by race.⁹⁹ I modify my updated model to allow the effect of disadvantaged status to vary by race and find that my conclusion (that there is no evidence of bias against Asian-American applicants) is not sensitive to this change. Although the average marginal effect across the six years becomes slightly more negative, it is still statistically indistinguishable from zero and there is still a mix of positive and negative effects across the six years (see Exhibit 15).

Exhibit 15

There is no consistent or statistically significant evidence of bias against Asian-American applicants even when the effect of disadvantaged status is allowed to vary by race

Class	Average Marginal Effect of Asian-American Ethnicity (Not Statistically Significant)
1. 2014	-0.46
2. 2015	-0.13
3. 2016	-0.01
4. 2017	0.05
5. 2018	-0.53
6. 2019	0.21
Overall	-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 relative to White applicants using the updated Card model with interaction of race and indicator for disadvantaged. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

109. Third, Prof. Arcidiacono disagrees with how I have used the available extracurricular activity information in the Harvard database. He complains that two of my modeling decisions—aggregating the 29 activities into 12 groups and omitting hours spent on activities other than work—cause me to understate the estimated effect of Asian-American ethnicity.¹⁰⁰ The variables he uses in place of mine have their own limitations, however. For example, Prof. Arcidiacono uses a coarse measure of hours of participation, which fails to identify the students most committed to a particular activity, and his measure of years of participation in a given activity gives equal weight to all instances of participation, regardless of the seriousness of the student’s commitment. These features appear to reward breadth of participation slightly more than depth. While I disagree with a number of Prof. Arcidiacono’s decisions about how to use the available information about applicants’

⁹⁹ Prof. Arcidiacono also includes in his preferred model a number of other interaction variables, such as allowing the effect of race or intended concentration to vary by gender, or allowing the effect of having a missing alumni interview rating to vary by race. I do not include these interaction terms in my model. As I discussed in my initial report, the choice to include interactions should be informed by a clear economic theory or methodological goal since there are hundreds of potential interactions one could add to the admissions model (Card Report, p. 49).

¹⁰⁰ Arcidiacono Rebuttal, pp. 40–41.

extracurricular activities from the database, I modify my updated model to incorporate his activity variables and show that I still find no evidence of bias against Asian-American applicants. (See Exhibit 16.)

Exhibit 16

There is no consistent or statistically significant evidence of bias against Asian-American applicants even when Prof. Arcidiacono’s preferred measures of extracurricular activity participation are used

Class	Average Marginal Effect of Asian-American Ethnicity (Not Statistically Significant)
1. 2014	-0.39
2. 2015	-0.05
3. 2016	0.09
4. 2017	-0.03
5. 2018	-0.44
6. 2019	0.16
Overall	-0.11

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 the updated Card model with Prof. Arcidiacono’s preferred measures of extracurricular activity participation. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

110. Prof. Arcidiacono criticizes my choice to include an applicant’s total hours worked but exclude hours spent on other activities because work activities “are only the eighth most popular activity listed for whites,” and elevating work above other extracurricular activities “distorts the analysis” since White applicants work more hours than Asian-American applicants.¹⁰¹ I included this particular measure because the number of hours a student works in a job is a straightforward measure of a student’s socioeconomic status as I have previously discussed, and there are limited individual-specific measures of socioeconomic status available in the database. Crucially, Prof. Arcidiacono’s preferred measures of hours spent working (whether above or below median hours) cannot identify fully the degree to which there is variation among applicants in hours worked at a job.

111. Fourth, as discussed in Section 3.2.1 above, Prof. Arcidiacono criticizes my model because it includes parental occupation variables that he considers “unreliable,” primarily because they vary from one year to the next.¹⁰² Although my year-by-year model addresses his concern, I have also conducted a sensitivity where I classify parent’s occupation into a combined “missing or

¹⁰¹ Arcidiacono Rebuttal, p. 41.

¹⁰² Arcidiacono Rebuttal, pp. 31–33.

unstable” category if it falls in one of the five categories Prof. Arcidiacono claims are problematic due to their fluctuations over time (Other, Homemaker, Unemployed, Low Skill, and Self-Employed). Again, as demonstrated in Exhibit 17, my results are not at all sensitive to this decision, and my conclusion that there is no evidence of bias against Asian-American applicants is unchanged.¹⁰³

Exhibit 17

There is no consistent or statistically significant evidence of bias against Asian-American applicants even when I modify my parental occupation variables to address Prof. Arcidiacono’s critique

Class	Average Marginal Effect of Asian-American Ethnicity (Not Statistically Significant)
1. 2014	-0.43
2. 2015	-0.04
3. 2016	0.06
4. 2017	0.12
5. 2018	-0.43
6. 2019	0.27
Overall	-0.07

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 the updated Card model with modifications to parental occupation controls, grouping ‘Laborer (Unskilled)’, ‘Low Skill’, ‘Self-Employed’, ‘Unemployed’, ‘Homemaker’, and ‘Other’ as one occupation category. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

112. Fifth, Prof. Arcidiacono argues that the staff interview rating should not be included in the admissions model.¹⁰⁴ Although I disagree with excluding this information (as discussed in Section 3.2.3 above), doing so does not alter my conclusions—there continues to be no statistically significant evidence of bias against Asian-American applicants (see Exhibit 18).

¹⁰³ As mentioned earlier, Appendix B.1 presents results for an additional sensitivity that addresses Prof. Arcidiacono’s more technical critique about how I aggregated occupational categories.

¹⁰⁴ Arcidiacono Rebuttal, p. 66.

There is no consistent or statistically significant evidence of bias against Asian-American applicants even if staff interview ratings are excluded from the model

Class	Average Marginal Effect of Asian-American Ethnicity (Not Statistically Significant)
1. 2014	-0.50
2. 2015	-0.12
3. 2016	0.04
4. 2017	0.03
5. 2018	-0.49
6. 2019	0.31
Overall	-0.12

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

Note: Table shows average marginal effect of race on admission for Asian-American applicants relative to White applicants using the updated Card model removing the indicator for receiving a staff interview rating. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

4.2. Analysis of key subgroups of the data provides further evidence that there is no bias in Harvard's admissions process

113. In my initial report, I showed that there was a positive (though statistically insignificant) effect of Asian-American ethnicity for two key subgroups of Asian-American applicants: female applicants and applicants from California docket. (Recall that the Admissions Committee divides Harvard applicants into dockets based on the geographic region of each applicant's high school.) In that report, I explained that analysis of subgroups of applicants is a well-accepted method for helping assess whether an average unexplained gap between two groups of applicants is caused by discrimination or, instead, by unobserved differences between the two groups. In that report, I wrote the following:

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 admissions 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.¹⁰⁵

114. In his rebuttal, Prof. Arcidiacono attempts to counter the subgroup analysis I presented in my initial report with three main critiques, none of which is sound. First, he reiterates his main criticisms of my model. Second, he states that I have failed to show that these subgroups are “statistically different from [my] other findings.” Third, he states that his concerns with the rating combinations I use in my main model are exacerbated when I estimate my analysis at the subgroup level.¹⁰⁶ In the remainder of this section, I explain why these critiques are flawed, and why my key results hold.

115. First, in Section 3 above, I have extensively described the shortcomings of Prof. Arcidiacono’s criticisms of my main model. As explained, my model more accurately reflects the process Harvard actually uses to select among applicants. My model does not filter out any applicants in order to obtain a particular result. My model is also less subject to the omitted variable bias endemic in Prof. Arcidiacono’s analysis, and it properly considers the fullest possible set of criteria Harvard uses when selecting students.

116. Prof. Arcidiacono’s second complaint—that I have not tested for statistically significant differences between this subgroup and the overall main model—misses the point of the analysis. The goal of this analysis is to help distinguish between a hypothesis of bias and a hypothesis of unmeasured differences. If Harvard were in fact biased in its decisions, I would not expect to see a small, *positive* (though statistically insignificant) estimated effect of Asian-American ethnicity in two of the largest subgroups of Asian-American applicants (accounting for nearly two-thirds of Asian-American applicants). I would instead expect to see a robust pattern of negative bias across most Asian-American subgroups. Thus, the patterns I observe in my subgroup analysis are more consistent with the fact that different groups of applicants have different unobserved characteristics than with a theory of discrimination in which the admissions committee targets its animus to an arbitrary (and relatively small) subgroup of Asian-American applicants.

117. Finally, to respond to Prof. Arcidiacono’s concerns that the ratings combinations I used in my preferred year-by-year model are not robust to subgroup level analysis because of the small

¹⁰⁵ Card Report, p. 75.

¹⁰⁶ Arcidiacono Rebuttal, p. 44.

sample size, I replicate my results from the prior report, using my updated model which uses Prof. Arcidiacono’s ratings variables instead of ratings combinations. As Exhibit 19 and Exhibit 20 show, these results are robust to Prof. Arcidiacono’s concerns.¹⁰⁷

Exhibit 19

The estimated effect of Asian-American ethnicity is positive (though statistically insignificant) for Asian-American women

Class	Average Marginal Effect of Asian-American Ethnicity (Not Statistically Significant)
1. 2014	0.21
2. 2015	0.55
3. 2016	0.05
4. 2017	-0.01
5. 2018	-0.34
6. 2019	0.33
Overall	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 relative to White applicants using the updated Card model on the sample of female applicants. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

¹⁰⁷ There is also no evidence of bias against Asian-American applicants (and, if anything, evidence of a positive effect of Asian-American ethnicity) for female applicants and applicants from California within the sample Prof. Arcidiacono prefers (excluding applicants who are lineage, recruited athletes, children of Harvard faculty staff, or on the Dean’s or Director’s interest lists). See workpaper.

The estimated effect of Asian-American ethnicity is positive (though statistically insignificant) for Asian-American applicants from California

Class	Average Marginal Effect of Asian-American Ethnicity (Not Statistically Significant)
1. 2014	-0.03
2. 2015	0.63
3. 2016	0.60
4. 2017	0.12
5. 2018	0.45
6. 2019	0.12
Overall	0.32

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 the updated Card model on the sample of applicants applying from California docket. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

118. As discussed above in Section 3, Prof. Arcidiacono’s rebuttal report proposes a new theory that Harvard’s alleged discrimination against Asian-American applicants does not apply to the ALDC applicants he claims have a different admissions process because there is no negative gap in admission rates between White and Asian-American applicants in those groups. If one takes seriously Prof. Arcidiacono’s new claim that Harvard somehow discriminates only against some subgroups of Asian-American applicants, my analysis above shows that applicants from California and female applicants are also not discriminated against. Such applicants represent nearly two-thirds (64%) of all domestic Asian-American applicants to Harvard over the six classes from 2014 through 2019.¹⁰⁸ Prof. Arcidiacono does not explain how or why Harvard would discriminate only against Asian-American men from states other than California, and it would seem to be nonsensical for Harvard to run a costly and highly complex admissions process and only discriminate against Asian-American applicants from some states—excluding those from the state with the largest fraction of Asian-American applicants. A more sensible interpretation of the differences across subgroups in the effect of Asian-American ethnicity is that there are unobserved differences between various subgroups of candidates that cause the disparity to be positive for some, negative for others, and statistically indistinguishable from zero as a whole.

119. In sum, the subgroup results discussed above and in my initial report reveal patterns that are entirely inconsistent with systematic discrimination against Asian-American applicants. SFFA

¹⁰⁸ See workpaper.

and Prof. Arcidiacono have offered no coherent explanation or theory of bias to explain these patterns. Without any explanation or theory for why such a pattern of discrimination would exist, the fact that so many subgroups of Asian-American applicants show no evidence of bias is strong evidence in support of my broader claim that the small differences in admission between Asian-American applicants and White applicants are best interpreted as differences between the two groups of applicants in characteristics that are not perfectly measured by the admissions data, rather than by racial bias against Asian-American applicants.

4.3. Prof. Arcidiacono's new allegation of bias against docket with larger shares of Asian-American applicants lacks any causal credibility

120. Section 9.3 of Prof. Arcidiacono's rebuttal offers yet another new theory of how Harvard allegedly imposes racial "penalties." He claims that Harvard "could also impose racial preferences or penalties through indirect channels such as geographic preferences based on the demographics of the targeted areas."¹⁰⁹ In making this claim, Prof. Arcidiacono presents no documentary evidence of such behavior by Harvard. Nonetheless, he presents an analysis that purports to show that Harvard is biased against docket with a larger share of Asian-American applicants. Specifically, he alleges that Harvard penalizes applicants of *all* races, regardless of other qualifications and/or life experiences, simply because they come from docket that happen to have higher shares of Asian-American applicants.¹¹⁰ There are significant problems with this argument.

121. First, putting this claim in perspective shows just how unlikely and unfounded it is. The California docket (discussed in the previous section) are the domestic docket with the three largest shares of Asian-American applicants in the sample. These docket contain over 33,000 applicants, 61% of whom are *not* Asian-American.¹¹¹ Prof. Arcidiacono's claim is that Harvard penalizes each and every one of the applicants on these docket (and other docket with a high share of Asian-American applicants) as a way to impose a racially motivated penalty targeted at Asian-American applicants. The apparent logic here is that, rather than impose a direct penalty on Asian-American applicants, Harvard is penalizing large swaths of its applicant pool simply because they are from an area with a high share of Asian-American applicants. This is an ill-founded claim based on an unusual theory of discrimination. As I will discuss in more detail below, it is particularly unusual because the estimated effect of ethnicity for Asian-American applicants from the California docket is *positive* (though statistically insignificant). Why would Harvard admit Asian-American applicants on California docket at higher rates than White applicants from those docket with similar characteristics and then at the same time penalize applicants of *all* races on these docket in an

¹⁰⁹ Arcidiacono Rebuttal, p. 77.

¹¹⁰ Arcidiacono Rebuttal, p. 78.

¹¹¹ See workpaper.

attempt to discriminate against Asian-American applicants? Again, Prof. Arcidiacono offers no evidence that Harvard is pursuing such a strange policy.

122. His analysis also suffers from at least two empirical flaws. To understand these flaws, it is helpful to first explain how Prof. Arcidiacono performs this analysis. Prof. Arcidiacono starts by collecting the coefficients for each of the separate docket from his admissions model. These coefficients represent the average effect of being from a given docket on an applicant's probability of admission after controlling for other factors in the admissions model (within a given year). The proper way to interpret these coefficients is that they capture unobserved factors that are not in the admissions model, but that are specific to that docket, that might increase or decrease the applicant's probability of admission. For example, students from different dockets will be coming from different high schools, and, thus, may have different levels of preparedness. Those differences would be captured by the docket coefficients because "preparedness" is not a variable directly accounted for in the admissions model.

123. Prof. Arcidiacono then takes these coefficients from each docket, correlates them with the share of the docket that is Asian-American, and finds a negative correlation. Based on this analysis alone, he then asserts that this correlation shows a *causal* relationship between a docket's admission rate and the share of Asian-American applicants on the docket. A causal relationship of this sort would reflect a discrimination scheme in which Harvard penalizes whole dockets so that it can indirectly penalize Asian-American applicants.

124. The first fundamental flaw with this analysis is that it controls for *no other docket-specific characteristics*. The differences between dockets measured by the docket fixed effects could be due to any number of things: unobserved measures of school composition, socioeconomics, or even geographic proximity to Harvard. Prof. Arcidiacono's simple correlation analysis does not allow him to discern whether the different admission rates across dockets are due to the share of Asian-American applicants in that docket or any number of other things that differ across dockets.

125. One way to see the unreliable nature of Prof. Arcidiacono's finding is in Exhibit 21. In the first row, we see Prof. Arcidiacono's claim that an increase in the share of Asian-American applicants on a docket causes Harvard to discriminate against everyone in that docket. In the second row, using the exact same approach, I show that Harvard has an even more intense "bias" against dockets with a high share of applicants who receive a guidance counselor rating of 1 or 2. In other words, taking Prof. Arcidiacono's analysis seriously, one would be forced to conclude that Harvard discriminates against students with strong ratings from guidance counselors by lowering the admission rate on dockets where they are most common. Of course, this is not true. The only plausible interpretation of the results in Exhibit 21 is, instead, that there are other features of each

docket that affect the admission rate that are correlated with receiving a strong guidance counselor rating and Asian-American ethnicity. This is yet another example of a common pattern in Prof. Arcidiacono’s empirical analysis—implementing analyses that do not control for relevant factors and then interpreting the results as evidence of bias against Asian-American applicants.

Exhibit 21

Simple changes to Prof. Arcidiacono’s analysis of docket-level bias show that his allegations are not credible

	Specification	Coefficient
1.	Docket-Year Fixed Effects on Share of Asian-American Applicants	-1.71 *
2.	Docket-Year Fixed Effects on Share with Guidance Counselor Rating of 1 or 2	-2.27 *

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

Note: Docket-year fixed effects are obtained from Prof. Arcidiacono’s preferred admissions model estimated using applicants to the classes of 2014 – 2019 who are in his expanded sample excluding athletes. Regressions of docket-year fixed effects on shares also contain year fixed effects. * indicates significance at the 5% level.

126. Perhaps more importantly, if Harvard were in fact trying to penalize Asian-American applicants from specific dockets where they are most highly concentrated, a much more plausible scenario would be that Harvard would “raise the bar” a bit higher for *only* the Asian-American applicants from those dockets—rather than imposing a penalty on the majority of applicants, who are not Asian-American, in those dockets. In fact, this is a theory that I explored in my first report and again in Section 4.2 of this report. The proper way to test such a theory is to estimate the full admissions model (controlling for as much information as possible) on applicants from such dockets, and then test whether there is any evidence of a larger disparity between White and Asian-American applicants in the dockets where Asian-American applicants are more concentrated. As I showed in my first report (and again in Section 4.2 above), that analysis shows that, if anything, Asian-American applicants are admitted at slightly higher rates relative to similarly qualified White applicants in the California dockets where they are most concentrated.

127. It is difficult to imagine a plausible theory of bias against Asian-American applicants whereby Harvard would penalize *all* applicants from dockets with high concentrations of Asian-American applicants as a way to indirectly penalize Asian-American applicants relative to White applicants, yet simultaneously treat Asian-American applicants *in those same dockets* a bit better than White applicants. Given the patterns in the data, Prof. Arcidiacono’s theory is simply not credible.

4.4. Other technical criticisms of my model do not change my findings

128. Prof. Arcidiacono also offers a handful of minor technical critiques of my methodology that do not affect my conclusions. For example, he criticizes my decision to include all applicants (including those for whom admission or rejection is perfectly predicted) in my average marginal effect calculation, and my decision to model profile ratings using variables that reflect specific combinations of the four profile ratings as opposed to modeling the effect of each profile rating separately. In this section, I address these criticisms.

129. Prof. Arcidiacono disagrees with my decision to calculate an average marginal effect over *all* domestic applicants. Specifically, he argues that I should exclude from my calculation applicants who are not competitive, i.e., those who have a marginal effect of race that is zero due to the fact that their rejection is perfectly predicted by one of the variables in the model.¹¹² He argues that including such applicants is misleading and causes me to “dilute the estimates of preferences by including many applicants whose characteristics are such that rejection is assured.”¹¹³ He further states that “[a] conservative position would be to focus the testing for racial preferences or penalties on all of those applicants who are not immediately ruled out—which would mean removing perfect predictions.”¹¹⁴ While this is a minor point, there are a number of problems with Prof. Arcidiacono’s arguments.

130. First, it is important to note that this decision has no effect on the average marginal effect of Asian-American ethnicity in my updated model. As shown above in Exhibit 13, the effect remains the same when I account for perfectly predicted applicants in my marginal effect calculation.

131. Second, Prof. Arcidiacono seems to be confused, because what I did in my first report (and continue to do in this report) is *exactly* what he says I should do. Although the average marginal effects reported in my initial report reflect an average that includes all applicants, the statistical test I conduct to determine whether the effect is statistically indistinguishable from zero is based *only upon applicants who are not perfectly predicted*, i.e., the applicants Prof. Arcidiacono says the test should be based on. This means that the results of my statistical test are the same whether or not I include people who are perfectly predicted in the calculation of my average marginal effect. Additionally, as just noted, the average marginal effect does not substantively change.

132. Third, contrary to Prof. Arcidiacono’s assertion, I include in my average marginal effect

¹¹² For example, in my model, if every single applicant with an academic rating of 5 in a given year were rejected, applicants with an academic rating of 5 in that year would be “perfectly predicted” and thus the marginal effect of their ethnicity (whether it be Asian-American or something else) would be zero.

¹¹³ Arcidiacono Rebuttal, p. 18.

¹¹⁴ Arcidiacono Rebuttal, p. 18.

calculation (but not my statistical test) not only the least competitive applicants (those whose rejection is perfectly predicted) but also *the most competitive applicants* (those whose admission is perfectly predicted). While there are far fewer applicants who are perfectly predicted to be admitted, contrary to Prof. Arcidiacono’s claim, my approach was not one-sided in the sense that it only included uncompetitive applicants. I included both the most competitive and the least competitive applicants in my reported average marginal effect.

133. Prof. Arcidiacono also disagrees with my decision to control for combinations of the four profile ratings in my year-by-year models. He argues that my approach “works to conceal the true effect of racial preferences,”¹¹⁵ yet his own analysis shows that using combinations of ratings as control variables changes the average marginal effect of Asian-American ethnicity by only 0.02 percentage points relative to his method (when using his model with the personal rating, which, as discussed in Section 3, omits a number of key variables).¹¹⁶ As I explained in my initial report, I use these ratings combinations variables in my year-by-year models not to “conceal the true effect of racial preferences” but because there is not enough data to estimate separately the effect of specific ratings that are very rare in the data due to limited sample size (e.g., personal ratings of 1), and to allow my model to account for any additional weight Harvard places on specific combinations of ratings. To ensure that this decision did not impact my findings, I also conducted a sensitivity analysis in my initial report where I ran a pooled model two ways—using ratings combinations and using Prof. Arcidiacono’s preferred ratings variables—and showed that the results were the same.¹¹⁷

134. Finally, as discussed in Section 4.1, despite his criticisms of my use of ratings combinations as control variables, Prof. Arcidiacono changed his own ratings variables in his new report to allow them to account for specific combinations of ratings, just as I did in my original model. As noted above, given this change, I have adopted his ratings variables for all of the regressions in this report to eliminate any further claims that those variables are the cause of the different conclusions we reach. They are not.

¹¹⁵ Arcidiacono Rebuttal, p. 64.

¹¹⁶ Arcidiacono Rebuttal, p. 73, Table 8.2N.

¹¹⁷ Card Report, p. 48, footnote 84.

5. THE EVIDENCE IS NOT CONSISTENT WITH ADMISSIONS DECISIONS BEING DETERMINED BY RACE ALONE

135. In my initial report, I presented a variety of analyses that explored whether race was a “determinative” factor in admissions. As I discussed in my original report, while race does have a significant effect on the probability of admission for some applicants, the data also show that—consistent with Harvard’s whole-person admissions process—each candidate who is admitted to Harvard has multiple dimensions of quality. These facts about Harvard’s admissions process are not consistent with race being a “determinative” factor in admissions.

136. In his rebuttal, Prof. Arcidiacono argues that race is “determinative” because race can have a relatively large effect on admissions for the subset of applicants who are highly competitive.¹¹⁸ As I explain in this section, Prof. Arcidiacono has interpreted the data incorrectly. Specifically, I show below that (a) race has limited explanatory power by itself, (b) race has less explanatory power than other key variables in the full regression model, (c) the marginal effect of race is very small for almost all applicants, and (d) variables other than race can have a large (or even larger) effect on admissions for individual applicants. All of these patterns are consistent with the fact that, to be admitted to Harvard, applicants must have *multiple* areas of strength, and race is not a determinative factor.

5.1. Race alone is uninformative in Harvard’s decision process

137. In my initial report, I included an analysis that measured how well different factors in the admissions process helped explain Harvard’s admissions decisions. Specifically, I showed that a model that considered only race had almost no explanatory power—a Pseudo R-Squared of just 0.002. By contrast, models that include only information on the student’s socioeconomic background were much more powerful, and models that include only student profile ratings were even more powerful (Pseudo R-Squared equal to 0.33).¹¹⁹ What these analyses establish is that race alone does not determine whether or not an applicant is admitted, and numerous other characteristics, on their own, are much better predictors of Harvard’s admissions decisions.

138. Prof. Arcidiacono responded to this analysis by asserting that: 1) a model with only race as an explanatory variable should be expected to perform poorly, and 2) the fact that race alone

¹¹⁸ Arcidiacono Rebuttal, pp. 49–51.

¹¹⁹ Card Report, p.83, Exhibit 27.

explains very little about admissions decisions actually suggests that racial preferences are, somehow, quite large.¹²⁰ Prof. Arcidiacono explicitly states that “[i]n order to properly evaluate the role of race in the admissions process, it is *paramount* that one controls for the relevant factors in the admissions decision.”¹²¹ This statement from Prof. Arcidiacono highlights a central difference in how Prof. Arcidiacono and I quantify the relative importance of race in Harvard’s admissions process. Prof. Arcidiacono is focused on whether race can have a relatively large effect for some candidates, *once we account for their other qualifications and/or life experiences*. However, as I explained in my first report, if race alone truly determines whether any individual applicant is admitted, then knowing that applicant’s other characteristics should not matter. The fact that 91% of African-American applicants and 93% of Hispanic applicants are not admitted indicates that other qualities besides race are highly relevant in determining who is and is not admitted.¹²² Prof. Arcidiacono’s acknowledgement that he needs to know the other characteristics of each applicant to assess the importance of race is an explicit recognition that no single factor in the admissions process (including race) is determinative.

139. Nonetheless, I modify my analyses from my initial report to address Prof. Arcidiacono’s concerns. I estimate my updated model that includes all factors (not just one factor at a time as I did in my previous report) and then calculate how the model’s explanatory power (as measured by Pseudo R-Squared) would change if I were to remove the effect of factors (such as race) one at a time. This exercise allows me to respond directly to Prof. Arcidiacono’s critique, by seeing how much explanatory power the model loses when race is excluded, compared to excluding other important factors from the model.

140. Exhibit 22 shows the Pseudo R-Squared for my updated model as well as for my updated model after removing the explanatory power of several different factors (such as race) one at a time. The results of this exercise are unambiguous. Unsurprisingly, the removal of race has the least effect on the explanatory power of the model. For example, turning off the effect of the teacher and alumni ratings reduces the model’s explanatory power by 50%, but turning off the effect of race causes a drop of only 10%. Turning off other factors, such as the academic, personal, or extracurricular ratings, also have a larger impact on the model’s explanatory power than race. This pattern is completely inconsistent with Prof. Arcidiacono’s assertion that race is a central factor in the admissions model; other factors are clearly more important.

¹²⁰ Arcidiacono Rebuttal, p. 48.

¹²¹ Arcidiacono Rebuttal, p. 49.

¹²² See workpaper.

Race explains far less about admissions decisions than other key factors such as ratings

Specification	Pooled Pseudo R-Squared		
	Value	Change	Percent Change
1. Card Model	0.64		
2. Removing Only Race Effect	0.57	-0.07	-10%
3. Removing Only Academic Rating Effect	0.53	-0.11	-17%
4. Removing Only Extracurricular Rating Effect	0.55	-0.08	-13%
5. Removing Only Personal Rating Effect	0.52	-0.12	-19%
6. Removing Only Teacher and Alumni Rating Effects	0.32	-0.32	-50%

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 expanded sample including athletes. Predicted probabilities are computed separately each year, from which the pooled Pseudo R-Squared values are computed.

5.2. The fact that race has a relatively large effect on the probability of admissions for some candidates cannot be taken as evidence that race is “determinative”

141. Prof. Arcidiacono further argues that my original report “misleadingly” focuses on uncompetitive applicants, which purportedly obscures the larger effect of race for competitive applicants.¹²³ He then points to the relatively large effect of race for the subset of African-American applicants who are most competitive as evidence that race is determinative for those applicants.¹²⁴ As I have discussed both in this report and in my original report, in order to reliably test for the alleged racial bias against Asian-American applicants, it is important to consider the full population of applicants, rather than strategically select particular cases. In fact, observing the number of students for whom race does not have an effect is a way to understand the upper limit of how important a single characteristic can be. Thus, I continue to find that it is highly relevant to the issues in the case that race has little to no effect on the admission outcomes for the vast majority of applicants to Harvard.

142. Despite that, in this section, I consider the additional question of whether the relatively large effect of race that exists for the subset of highly competitive applicants should be taken as evidence that race is determinative even for them. As I discuss below, it should not. The reason is that, because Harvard assesses a wide variety of characteristics across all students, it turns out that *many* distinguishing characteristics (whether race or another trait) will produce a more powerful

¹²³ Arcidiacono Rebuttal, p. 49.

¹²⁴ Arcidiacono Rebuttal, p. 51.

effect for students on the margin of being admitted or not admitted.

143. To help understand these points, consider Exhibit 23 below. In this exhibit, I compare the average marginal effect of several different characteristics. In particular, I compare the size of the marginal effect associated with being African-American or Hispanic to the size of the marginal effect for several non-racial characteristics, including being a lineage applicant, or receiving a top profile rating (academic, personal, or extracurricular). I adopt Prof. Arcidiacono’s method of looking at the marginal effect for each decile of the admissions index, and show the relative effect of each characteristics on the probability of admission within each decile.

Exhibit 23

The effect of race follows the same pattern across deciles as other characteristics in Harvard’s admissions process

Predicted Probability of Admission Decile	Average Marginal Effect					
	African-American Applicants	Hispanic or Other Applicants	Lineage Applicants	Applicants with an Academic Rating of 1	Applicants with an Extracurricular Rating of 1	Applicants with a Personal Rating of 1
1. 1 (Weakest)	0.00	0.00	0.00	0.00	0.01	0.01
2. 2	0.02	0.00	0.02	0.13	0.08	-
3. 3	0.12	0.02	0.08	1.03	0.39	0.00
4. 4	0.44	0.09	0.25	3.56	1.32	0.79
5. 5	1.26	0.26	0.66	8.39	3.98	-
6. 6	3.39	0.72	1.69	17.43	9.82	2.10
7. 7	9.08	2.00	4.37	40.42	21.88	27.61
8. 8	24.01	6.08	12.02	65.32	45.69	45.72
9. 9	53.04	21.49	32.55	78.98	70.80	49.86
10. 10 (Strongest)	41.28	30.34	26.34	43.20	39.74	21.58

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 expanded sample including athletes. Deciles are constructed by year, across the full sample, based on the predicted probabilities of admission after removing the effect of the given characteristic. Marginal effects are computed for applicants with the given characteristic relative to the baseline (i.e. White, non-lineage, academic rating of 3, extracurricular rating of 3, and personal rating of 3). Marginal effects are reported as percentage point values. “-” indicates that there are no applicants with a given characteristic in a given decile.

144. The pattern here is clear. For most characteristics, the marginal effect of that characteristic is highest for candidates in the top admissions deciles. This is a natural consequence of the fact that Harvard places a very high value on multiple dimensions of quality, rather than on any single attribute. For candidates in the lower deciles (who have relatively few observed characteristics that Harvard values), the “tip” for African-American race, or for being a lineage applicant, or for having a profile rating of 1 is very small, because having just one major strength is not enough to ensure a high probability of admission. Candidates in the upper deciles, on the other hand, are relatively strong on at least one dimension, and in most cases several dimensions, that Harvard values. For these candidates, the extra “tip” for any one additional strength can be large. Importantly, the pattern that Prof. Arcidiacono demonstrates for race—the largest effects concentrated among the strongest candidates—is present for other characteristics in Exhibit 23, such as being a lineage

applicant or a candidate with a top profile rating.

145. If we compare the patterns of the effect of race specifically with the pattern of the effect of receiving an academic or extracurricular rating of 1, a notable finding is that the effect of a top academic or extracurricular rating is both larger and more widespread across the full distribution of applicants than the effect of race. If race were truly “determinative” then we would not expect to see other factors with a larger effect than race, and we would not expect to see such a small effect for race among the least competitive applicants. The fact that we do means that the incremental value of race is smaller than the incremental value of having a top academic or extracurricular rating. Such patterns are consistent with race being one of many factors that can help distinguish a candidate—not the only one (or even the most important one).

146. Exhibit 24 presents another way to see this same point for African-American candidates—the group of candidates Prof. Arcidiacono focuses on most. Exhibit 24 demonstrates two important facts. First, it shows that the effect of race is small (9 percentage points or less) for the vast majority of African-American applicants (those in deciles 1 to 7).¹²⁵ This can be seen in the second column, which reports the average marginal effect of race for African-Americans. Second, it shows that for the subset of African-American applicants for whom the marginal effect of race is largest (applicants in the 9th and 10th admissions index deciles), the marginal effect of ratings is substantially larger than the marginal effect of race. For the strongest applicants (those in the 10th decile of the admissions index), the effect of ratings is almost twice the size of the effect of race.

¹²⁵ Note that I use Prof. Arcidiacono’s preferred approach of constructing the index across all races, not just African-American applicants. 86.4% of all African-American applicants are in deciles 1 to 7. See workpaper.

The effect of race is smaller than that of ratings for African-American applicants

African-American Applicants			
Predicted Probability of Admission Decile	Average Marginal Effect of Race	Average Marginal Effect of All Ratings	Admission Rate
1. 1 (Weakest)	0.00	0.00	0.00%
2. 2	0.02	0.01	0.00%
3. 3	0.12	0.06	0.06%
4. 4	0.44	0.30	0.16%
5. 5	1.26	1.03	0.59%
6. 6	3.39	3.09	3.25%
7. 7	9.08	8.90	11.59%
8. 8	24.01	24.39	27.76%
9. 9	53.04	58.03	63.24%
10. 10 (Strongest)	41.28	72.44	87.76%

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 expanded sample including athletes. Deciles are constructed by year, across the full sample, based on the predicted probabilities of admission after removing the effect of race. All ratings include the four profile ratings, teacher and guidance counselor ratings, and alumni ratings. Marginal effects are computed for African-American applicants relative to the baseline (i.e. White, and ratings of 3 for applicants with ratings of 1 and 2). Marginal effects are reported as percentage point values.

6. DOCUMENTS AND HARVARD'S DATA UNDERMINE PROF. ARCIDIACONO'S CLAIM THAT HARVARD IMPOSED A FLOOR ON THE ADMISSION RATE FOR SINGLE-RACE AFRICAN-AMERICAN APPLICANTS STARTING WITH THE CLASS OF 2017

147. In his first report and again in his rebuttal, Prof. Arcidiacono claims that Harvard manipulated its admission rates to create a floor on the admission rate for single-race African-American applicants starting with the class of 2017. His only empirical evidence of this claim is the fact that the difference between the admission rate for single-race African-American applicants and all other applicants was very small for the classes of 2017, 2018, and 2019 using the IPEDS definition of race.¹²⁶ As I explained in my first report, Prof. Arcidiacono's claim of manipulation is not supported by any other evidence in the record. In this section, I highlight three critical reasons to be skeptical of Prof. Arcidiacono's claim.

148. First, Prof. Arcidiacono has substantially changed his theory for why Harvard would manipulate the African-American admission rate. For example, in his initial report, Prof. Arcidiacono claimed that, “[f]or the class of 2017 and going forward, Harvard adopted a new methodology for coding race and ethnicity that was consistent with federal standards for reporting of race and ethnicity,” and that because this “new” methodology excluded multi-racial African-American students from the “African-American” category, this change “prompted concern at Harvard that the new reporting would understate the number of African-American admits to Harvard.”¹²⁷ As a result, he asserted that Harvard imposed a floor on single-race African-American admissions. In response to my pointing out that the documents did not support this claim (including the fact that Harvard adopted the methodology at issue three years *before* the class of 2017),¹²⁸ in his rebuttal Prof. Arcidiacono shifts the catalyst from alleged public concern, to potential concern from admissions officers at peer institutions who participate in particular cross-institutional meetings (discussed below). As I explain below, his argument continues to rest on a selective reading of the available documents and appears to be an attempt to justify *ex post* his alleged finding of “manipulation” in a particular set of years for a particular racial group.

149. Second, it is important to understand that the pattern Prof. Arcidiacono identifies as evidence of manipulation can be easily explained by random chance. Given that Harvard has at least three operative definitions of race (New Methodology, Old Methodology, IPEDS) and several racial groups under each definition, finding three years in a row in which one racial group's admission rate is close to the overall admission rate is not as unlikely as Prof. Arcidiacono suggests. Yet Prof. Arcidiacono takes this expected pattern in the data, attempts to fit certain facts around it, and then

¹²⁶ Arcidiacono Report, pp. 27–30.

¹²⁷ Arcidiacono Report, pp. 27–28.

¹²⁸ Card Report, pp. 88–89.

claims it is evidence of manipulation.

150. Finally, Prof. Arcidiacono's new argument that the relative quality of single-race African-American admitted students fell starting with the class of 2017 is not supported by his own analysis. As I show below, he makes a statistical error that when corrected undoes his results.

6.1. The record does not support Prof. Arcidiacono's claim of a floor on single-race African-American admissions starting with the class of 2017

151. In my initial report, I identified several reasons why Prof. Arcidiacono's claim that Harvard began to manipulate the African-American admission rate with the class of 2017 did not make sense. Specifically, I explained how Harvard adopted the IPEDS methodology for federal reporting three years *before* the alleged floor was implemented, and that the documents Prof. Arcidiacono cited did not demonstrate particular concern from Harvard about public perceptions of the single-race African-American admission rate starting in 2013 (the class of 2017 admissions cycle). Indeed, the record shows that Harvard does not even use IPEDS when reporting statistics on race to the press and public. Using Harvard's preferred and most commonly used methodology for classifying race, I demonstrated that the racial composition of the Harvard class does fluctuate somewhat year to year. I also showed that, inconsistent with a floor on the rate of admissions, the relative quality of African-American admitted students did not fall starting with the class of 2017.¹²⁹

152. In his rebuttal, Prof. Arcidiacono stands by his general claim, stating that it "is certain—and undisputed—that Harvard was purposely taking steps to ensure that the admission rate of single-race African-American applicants approximated or exceeded the overall admission rate of other domestic applicants."¹³⁰ In addition, he modifies his story for why Harvard would choose to manipulate these admission rates, suggesting that perhaps Harvard's participation in admissions industry group meetings for COFHE and ABAFAOILSS precipitated the alleged floor on admission.¹³¹ Prof. Arcidiacono does not offer any evidence on these points, relying instead on speculation without any basis in fact. Below I highlight several flaws in his theories.

153. First, despite Prof. Arcidiacono's assertion that "Harvard was *purposely* taking steps"¹³²

¹²⁹ Card Report, pp. 87–93.

¹³⁰ Arcidiacono Rebuttal, p. 9; Card Report p. 88.

¹³¹ Arcidiacono Rebuttal, p. 57.

¹³² Arcidiacono Rebuttal, p. 9 (emphasis added).

to bring about this statistical phenomenon, his report is notable for its lack of any direct evidence of motivation or intent on the part of Harvard. The main motivation he posits for why Harvard would manipulate the admission rates is that Harvard was “very concerned about criticisms tied to its IPEDS data at the precise time the first evidence of the floor appears in the data.”¹³³ This claim follows the pattern of the claims in his first report, where he motivated his analysis with the unsubstantiated assertion that the IPEDS methodology “prompted concern at Harvard that the new reporting would understate the number of African-American admits to Harvard,” and that this concern led to Harvard implementing a floor.¹³⁴ However, Prof. Arcidiacono does not present a single “criticism tied to [Harvard’s] IPEDS data” that might have precipitated the alleged floor on African-American admissions. Again, Harvard had been reporting IPEDS figures to the federal government for years before allegedly implementing the floor, and Harvard released information on the racial composition of the admitted class to the public using its preferred “New Methodology” for classifying race—not IPEDS.¹³⁵

154. In lieu of direct evidence that Harvard was facing criticism for its use of IPEDS data, Prof. Arcidiacono cites several documents that he claims provide evidence that Harvard was “very concerned about the way its IPEDS enrollment numbers were being perceived by the public in early 2013.”¹³⁶ In these documents, Harvard officials discuss how data on race are collected, and express the view that the IPEDS method for classifying race can be “confusing” and “misleading” since it does not always align with how students identify their own race. These documents provide no evidence that Harvard’s concerns about racial statistics led it to manipulate admission rates.¹³⁷

155. In his rebuttal, Prof. Arcidiacono also introduces and emphasizes the fact that Harvard

¹³³ Arcidiacono Rebuttal, p. 9.

¹³⁴ Arcidiacono Report, pp. 28–30.

¹³⁵ Card Report, pp. 88–89.

¹³⁶ Arcidiacono Rebuttal, pp. 56–57.

¹³⁷ Prof. Arcidiacono cites the following material in support of his claim: “Addendum on the collection and reporting of data on race and ethnicity,” HARV00030509 – 12 at HARV00030511. This memo discusses how demographic data is reported by IPEDS, and how the IPEDS methodology differs from Harvard’s preferred method for reporting race. It is an edited version of HARV00023592 – 4, which Prof. Arcidiacono also cites. Both versions of the document explain that “the IPEDS reporting system leads to significantly underreporting percentages for **all ethnicities** except Hispanic Americans. The method used by Harvard and many peer institutions gives a more complete report of the way many students, especially those of mixed heritage, actually view their racial and ethnic identities” (at HARV00023594 and HARV00030510 – 11, emphasis added); Email from Jeff A. Neal to William R. Fitzsimmons et al., “FW: Draft Annual Admissions Applications Gazette Article,” February 6, 2013, HARV00023588 (“It explains the difference between what’s reported in IPEDS (basically, all students get one ethnicity and they all add up to 100%) and what [Harvard] report[s] publically (students pick as many ethnicities as they think apply to themselves and all [Harvard’s] students’ ethnicities add up to more than 100%).”).

has long participated in COFHE meetings and ABAFAOILSS “Round Robins” in which admissions officers from various colleges and universities share, confidentially, statistics about race and admissions.¹³⁸ He documents that Harvard officials attended these meetings and shared data on race and admissions. He then implies that the exchange of information at those meetings somehow created an incentive for Harvard to introduce a floor on African-American admissions.¹³⁹ But he offers no documents or testimony to support this implication.

156. Indeed, nothing in the record supports Prof. Arcidiacono’s arguments that these meetings encouraged universities to implement racial quotas. Christina Lopez, a representative for ABAFAOILSS, testified that the point of Round Robins is for universities to share information and best practices with respect to diversity and recruiting.¹⁴⁰ A primary mission of ABAFAOILSS is “sharing best practices across [its member] institutions to ensure equity and inclusion.”¹⁴¹ The evidence further shows that Round Robins were a way for universities to disseminate helpful information on successful recruiting tactics, like which particular cities, schools, and community-based organizations seem to yield strong under-represented applicants.¹⁴² The fact that Harvard admissions officers attended these meetings is indicative of Harvard’s commitment to recruiting under-represented applicants—not evidence that it allegedly manipulated admission rates.

157. In sum, none of the documentary evidence presented by Prof. Arcidiacono convincingly indicates that “Harvard was very concerned about criticisms tied to its IPEDS data at the precise time

¹³⁸ Arcidiacono Rebuttal, p. 57; COFHE Admissions Statistics, Class Entering 2013, HARV00004683 – 4789; Deposition of Christina Lopez, May 22, 2017 (“Lopez Deposition”), pp. 57–59 (“As stated in the constitution, information that is shared is to be used as confidential... Q. Why is this information confidential? ... A. Enrollment information for colleges is not public information.”).

¹³⁹ Arcidiacono Rebuttal, pp. 56–57.

¹⁴⁰ Lopez Deposition, p. 53 (“Q. I want to ask a few questions about the Round Robin meetings. What are the Round Robin meetings? A. Round Robin is a separate—it is a part of our meetings where we share enrollment and application numbers. Q. And what is the purpose of a Round Robin? A. The purpose is to share best practices as well as recruitment information across institutions.”).

¹⁴¹ Lopez Deposition, p. 21 (“Our mission is to work for access for under-represented students in higher education as determined by our constitution, providing access and sharing best practices across our institutions to ensure equity and inclusion of under -- for historically under-represented groups in higher education”), p. 36 (“The mission of ABAFAOILSS is to maintain, increase, and solidify access in equity for under-represented students in higher education, as well as provide a space for those who serve within those admissions offices to have a space to share of their experiences serving in those capacities and within their office.”).

¹⁴² Lopez Deposition, p. 80 (“If a school is doing recruitment in a certain state and they have found that their recruitment strategy in terms of bringing in group travel with other schools or hitting a certain city and community-based organizations is producing strong applicants, then other schools may want to know where those particular places are and also include those in their strategies as well. If I found a school that was doing great work, I would want to share that with my colleagues.”).

the first evidence of the floor appears in the data.”¹⁴³

6.2. *The pattern that Prof. Arcidiacono claims as evidence of manipulation is not as unlikely as he suggests*

158. Given the lack of a clear incentive or motivation for Harvard to manipulate admission rates, a basic threshold question for Prof. Arcidiacono’s claim is: are the alleged “manipulated” patterns in the data sufficiently rare that they cannot be explained by random chance? As I discuss below, Prof. Arcidiacono’s claim does not surpass this basic threshold.

159. First, it is important to note that the more outcomes and data points that can be examined in a search for evidence of an alleged floor on admissions, the greater the probability of finding such a pattern just by chance. Indeed, this fundamental observation is the basis for widespread concerns in the research community over “data mining.”¹⁴⁴ Prof. Arcidiacono himself acknowledges this fact, noting that the array of outcomes one could search over to find alleged evidence of a quota is vast: “[T]here are undoubtedly many ways Harvard could impose racial floors. They could impose a floor based on the expected number of admits, the share of admits of a particular race, or the relative acceptance rates of particular races. Alternatively, Harvard could impose a floor based on the expected number of enrollees of a particular race. Furthermore, Harvard could do this using a variety of different measures of race.”¹⁴⁵ That Prof. Arcidiacono found a pattern consistent with one of *many* prospective floors is not particularly surprising.

160. Second, the specific pattern Prof. Arcidiacono homes in on is not as unlikely as he suggests. Prof. Arcidiacono computes a very specific number in his initial report: the probability that the single-race African-American admission rate matched overall admission rate for the classes of 2017, 2018, and 2019, which he computes to be approximately 0.2%. He argues that this means there is a 0.2% probability that the correspondence between admission rates between 2017 and 2019 happened by chance.¹⁴⁶ It is important to remember that the available admissions data that Prof. Arcidiacono analyzes includes: six years of data, at least three operative definitions of race (New Methodology, Old Methodology, IPEDS), and several racial groups under each definition. Given these six years of data and three definitions of race, there is nothing surprising about finding three years in a row in which one racial group’s admission rate is close to the overall admission rate.

¹⁴³ Arcidiacono Rebuttal, p. 9.

¹⁴⁴ For example, see Garret Christensen and Edward Miguel, “Transparency, Reproducibility, and the Credibility of Economics Research,” NBER Working Paper #22989, December 2016, pp. 15–17.

¹⁴⁵ Arcidiacono Rebuttal, p. 56.

¹⁴⁶ Arcidiacono Report, p. 29.

161. Given that there are many racial groups and three-year periods to search over to find evidence of an alleged quota, Prof. Arcidiacono's estimate of 0.2% is likely to vastly understate the probability of finding such a coincidence in the data. For example, imagine that Prof. Arcidiacono were simply looking for a stretch of three years between 2014 and 2019 in which the admission rate for any particular racial group matched the admission rate for all other groups using either IPEDS, the New Methodology, or the Old Methodology. There are eight racial categories under the New Methodology, eight under the IPEDS methodology, and at least seven under the Old Methodology, for a total of 23 groups.¹⁴⁷ With 23 racial groups and four possible three-year stretches to search over, Prof. Arcidiacono has 92 opportunities (23 multiplied by four) to find the pattern of interest. Assume for the sake of simplicity that Prof. Arcidiacono's calculation is correct, and assume that for any given racial group and three-year stretch there is a 0.2% chance that that group's average admission rates match the admission rate for other applicants.¹⁴⁸ Because there are 92 combinations to check, not just one, the chances of seeing evidence of an alleged quota are actually much higher than 0.2%. Indeed, with 92 options to search over, the probability of seeing an allegedly "suspicious" three-year stretch simply by chance is about 17% (that is, one minus 99.8% to the 92nd power).¹⁴⁹ In other words: the probability that Prof. Arcidiacono would find evidence of his particular type of floor is likely much higher than the 5% threshold typically used to reject that an event occurred by chance. Furthermore, as I noted above in paragraph 159, this is only one of *many* types of floors that Prof. Arcidiacono states he could have searched over. Combined with the lack of any credible documentary evidence discussed above, a more reasonable interpretation of the patterns in the data is that they are due simply to chance.

6.3. The relative quality of single-race African-American admitted students did not fall starting with the class of 2017, further undermining the idea of a floor on their admission rate

162. As noted in my first report, if a floor was imposed on African-American admission rates, it would very likely generate a decline in the relative quality of African-American admitted students as compared to other admitted students. The data reflect no such decline, as I showed in my first

¹⁴⁷ The racial groups are as follows. New Methodology: White, Asian, Black, Hispanic (including Mexican and Puerto Rican), Native American, Native Hawaiian, multi-racial, and race unknown. IPEDS: White, Asian, Black, Hispanic (Including Mexicans and Puerto Ricans), Native Americans, Native Hawaiians, multi-racial, and race unknown. Old Methodology: White, Asian, Black, Hispanic (including Mexican and Puerto Rican), Native American (including Hawaiian), Other, Unknown. See, for example, "Ethnicity Backgrounds – Classes of 2014 – 2017," HARV00005106; "Applicants, Admits, and Matriculants – Old Methodology NLNA," HARV00001851 – 56 at HARV00001851.

¹⁴⁸ The probability could vary, but for illustrative purposes I assume it is fixed at 0.2% for all permutations.

¹⁴⁹ The calculation is: $1 - (1 - 0.002)^{(23 * 4)} = 16.8\%$.

report.¹⁵⁰

163. In his rebuttal, Prof. Arcidiacono responds to this analysis by presenting evidence that he claims shows a statistically significant decrease in the relative Academic Index of single-race African-American admitted students as compared to multi-racial African-American admitted students.¹⁵¹ Prof. Arcidiacono refers to this relative change in the Academic Index as the “double difference,” which he reports as statistically significant in his Table 6.2N.¹⁵² He then interprets this “double difference” as evidence that the relative quality of single-race African-American admitted students fell after 2017, consistent with a floor on single-race African-American admissions. He also notes that there is an allegedly significant increase in the relative admission rate of single-race African-American applicants versus multi-racial African-American applicants before and after 2017 (which he again refers to as the “double difference” in his table 6.3N).¹⁵³

164. Prof. Arcidiacono makes a critical calculation error in this analysis that, when corrected, reverses his key finding. Specifically, his calculations of the statistical significance of the “double differences” in his tables 6.2N and 6.3N are implemented incorrectly, resulting in standard errors that are too small. In other words, he overstates the precision of his estimates, which makes his results look statistically significant when they are not (see Appendix B.2). Once I correct this error, the “double differences” reported in tables 6.2N and 6.3N are not statistically significant at the 5% level (Exhibit 25). In other words, when Prof. Arcidiacono’s own analysis is done correctly, there is no statistically significant change in the relative admission rate of single-race and multi-racial African-American admitted students before and after 2017, nor is there a statistically significant change in the relative average Academic Index of single-race and multi-racial African-American admitted students before and after 2017.

165. Furthermore, the relative quality of single-race African-American admitted students did not fall as compared to that of multi-racial African-American admitted students on a more comprehensive array of metrics. Exhibit 25 mimics Prof. Arcidiacono’s analysis of the Academic Index in his Table 6.2N, but uses each of the four profile ratings, as well as the admissions index, which summarizes an applicant’s overall probability of being admitted according to my updated model. I remove the effect of race when computing the admissions index. For each characteristic, I report the difference between single-race and multi-race African-American admitted students in the period spanning 2014 – 2016, the period spanning 2017 – 2019, and the difference-in-difference between these two numbers (what Prof. Arcidiacono calls the “double difference”). If the difference-

¹⁵⁰ Card Report, p. 89.

¹⁵¹ Arcidiacono Rebuttal, pp. 59–60.

¹⁵² Arcidiacono Rebuttal, p. 60, Table 6.2N.

¹⁵³ Arcidiacono Rebuttal, p. 61, Table 6.3N.

in-difference is negative and significant (as denoted by a star), this suggests that the relative quality of single-race African-American admitted students fell.

166. I find that as measured by Harvard's four profile ratings and the admissions index (removing the effect of race), the relative strength of single-race African-American admitted students did not fall relative to the strength of multi-racial African-American admitted students after 2017. *None* of the difference-in-difference estimates in Exhibit 25 is statistically significant. This is highly inconsistent with there being a floor on the admission of single-race African-American students.

The relative quality of single-race African-American admitted students did not fall in 2017

	African-American Admitted Students		Difference [1]
	Single-Race	Multi-Race	
Admission Rate [2]			
1. Average 2014 – 2016	6%	10%	-3% *
2. Average 2017 – 2019	6%	8%	-2% *
3. Difference-in-Difference			2%
Average Academic Index [2][3]			
4. Average 2014 – 2016	0.20	0.19	0.01
5. Average 2017 – 2019	0.23	0.34	-0.12 *
6. Difference-in-Difference			-0.13
Fraction with Academic Rating of 1 or 2 [2]			
5. Average 2014 – 2016	53%	48%	5%
6. Average 2017 – 2019	55%	57%	-2%
7. Difference-in-Difference			-7%
Fraction with Extracurricular Rating of 1 or 2 [2]			
8. Average 2014 – 2016	47%	52%	-5%
9. Average 2017 – 2019	48%	49%	-1%
10. Difference-in-Difference			4%
Fraction with Personal Rating of 1 or 2 [2]			
11. Average 2014 – 2016	74%	76%	-2%
12. Average 2017 – 2019	74%	72%	2%
13. Difference-in-Difference			4%
Fraction with Athletic Rating of 1 or 2 [2]			
14. Average 2014 – 2016	20%	24%	-5%
15. Average 2017 – 2019	22%	28%	-6%
16. Difference-in-Difference			-1%
Average Admissions Index [4]			
17. Average 2014 – 2016	0.24	0.31	-0.07 *
18. Average 2017 – 2019	0.26	0.32	-0.06 *
19. Difference-in-Difference			0.01

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

Note: [1] * indicates statistical significance at the 5% level. [2] Consistent with Prof. Arcidiacono's analyses, data are from domestic admitted applicants, including prior admitted applicants and excluding deferred admitted applicants. [3] Academic Index values are in standard deviation units. Average Academic Index calculations exclude students with GPA flags. [4] Data are from admitted applicants in Prof. Arcidiacono's expanded sample including athletes (my preferred year-by-year regression model sample). The admissions index is constructed using applicants' predicted probability of admission after removing the effect of race.

167. In sum, Prof. Arcidiacono's assertions of a floor on African-American admissions are supported neither by the record nor by Harvard's data on applicant quality. The pattern Prof. Arcidiacono takes as evidence of an alleged floor could be due to chance, and he provides no credible documentary evidence to suggest otherwise. Furthermore, the data show no evidence of a decline in

the relative quality of the group that is allegedly receiving preferential admissions treatment—
undermining the idea that such a floor exists.

7. MR. KAHLENBERG DOES NOT SHOW THAT HARVARD COULD ACHIEVE A COMPARABLY DIVERSE AND HIGH-QUALITY CLASS WITHOUT CONSIDERING RACE

168. In my initial report, I analyzed a set of race-neutral alternatives proposed by SFFA and its expert, Richard Kahlenberg. Consistent with the existing economics literature on race-neutral alternatives—including the papers cited by Mr. Kahlenberg—I found that these policies were unlikely to increase diversity without diminishing the quality of Harvard’s admitted class and/or changing its characteristics in other ways that I understand matter to Harvard.¹⁵⁴ In his rebuttal, Mr. Kahlenberg presents three main critiques of my analysis. In this section, I address each in turn and explain why none affects the main conclusions of my first report.

169. First, Mr. Kahlenberg offers additional arguments from the economic literature on race-neutral alternatives. He asserts that the literature supports the claim that race-neutral alternatives can achieve diversity at low cost to quality at selective institutions.¹⁵⁵ As I explain below, none of the papers Mr. Kahlenberg cites, and none of the new arguments he advances, supports his claims. In fact, the papers he cites support the main conclusion from my first report: race-neutral alternatives reduce the ability of universities to admit students with other characteristics they value, with a particularly large effect for more selective institutions.

170. Second, Mr. Kahlenberg presents a series of criticisms of my simulations, and offers several new simulations of his own. As I show below, his criticisms of my simulations are either ill-founded or irrelevant. My core findings are robust to his suggested changes. Moreover, the new simulations presented by Mr. Kahlenberg actually underscore my initial findings: none of the race-neutral alternatives he offers generates a comparably diverse student body, and all result in larger changes to class quality than the version of my simulation Mr. Kahlenberg chooses as a benchmark, as measured by Harvard’s academic, personal, and extracurricular ratings, among other indicia.

171. Finally, Mr. Kahlenberg criticizes my analysis of expanding financial aid, recruiting efforts, and transfer admissions as race-neutral policies for increasing diversity, as well as my evaluation of eliminating deferred admission and using place-based admissions policies. I address each of his criticisms below.

¹⁵⁴ Card Report, p. 95.

¹⁵⁵ Rebuttal Expert Report of Richard D. Kahlenberg, *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College (Harvard Corporation)*, January 30, 2018 (“Kahlenberg Rebuttal”), pp. 2–5.

7.1. *The academic literature establishes that race-neutral alternatives diminish selective universities' ability to select on quality*

172. My initial report cited the extensive academic literature that finds that the use of race-neutral alternatives by selective universities necessarily comes with a meaningful cost to class quality.¹⁵⁶ Mr. Kahlenberg criticizes several papers that I rely on, but does not introduce any new academic articles beyond those cited in his and my initial reports. His criticisms do not alter or undermine the conclusions in my initial report. Below, I discuss each of those papers in light of Mr. Kahlenberg's criticisms, and explain how his additional criticisms about those papers are misleading.

173. My report cites a 2004 study by Carnevale, Rose, and Strohl, which finds that it is difficult for race-neutral alternatives to reproduce the level of racial diversity seen under admissions policies that directly consider race.¹⁵⁷ In his reply, Mr. Kahlenberg states that "Card fails to mention that ten years later, these same professors found two alternatives that produced *greater* racial diversity and *higher* mean SAT scores[.]"¹⁵⁸ However, in the 2014 paper Mr. Kahlenberg refers to, those authors heavily qualify these findings:

In the end, we find that "race-blind" and "race-conscious" (giving an added boost to underserved minorities) forms of affirmative action can substitute for the use of "race alone" in college admissions. But these alternatives are only available if elite colleges are willing to risk lower average test scores (in the case of two of our five simulations, one estimate is higher but not statistically significant) and thereby lower graduation rates.¹⁵⁹

174. In other words, ten years after their initial paper, Carnevale, Rose, and Strohl still conclude that considering race in the admissions process is the most efficient way to produce increased racial diversity. Further, they conclude that race-blind admissions policies do, indeed, come at a cost. Lastly, the researchers also caution that alternative approaches require "substantial

¹⁵⁶ Card Report, pp. 97–103.

¹⁵⁷ Card Report, p. 101.

¹⁵⁸ Kahlenberg Rebuttal, p. 4

¹⁵⁹ 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), ("Carnevale, Rose, and Strohl 2014"), pp. 187–202 at p. 188.

disruption in the admissions practices and enrollments of selective colleges.”¹⁶⁰

175. Mr. Kahlenberg also suggests that the studies I cited by Thomas Kane and Reardon et al., are too limited in scope to be insightful. He writes that “Card cites studies by Thomas Kane and Sean Reardon finding that using income instead of race in admission will not produce the same level of racial diversity” and states these are “of little value here because they measure only the use of income and not, as I propose, a broad set of socioeconomic variables[.]”¹⁶¹ This criticism is incorrect. First, Kane does discuss targeting “broader” socioeconomic indicators, and argues that given his findings, such policies were not likely to be much more successful. Second, Reardon et al. do not measure “only the use of income.” Rather, they look at the Texas Top Ten Percent Plan, which Mr. Kahlenberg champions, and conclude that it would lead to a 10% reduction in minorities attending selective schools.¹⁶²

176. Later, Mr. Kahlenberg discusses a paper by Mathew Gaertner, cited in both his earlier report and my report, about the costs to race-neutral alternatives.¹⁶³ Mr. Kahlenberg attempts to downplay Gaertner’s conclusion that race-neutral alternatives “are complicated to implement and may lower the academic quality of the admitted class and the likelihood of success for admitted students.”¹⁶⁴ In particular, Mr. Kahlenberg comments that, “Card fails to mention that Gaertner concludes low-income students do about as well academically as underrepresented minority students admitted through race-based affirmative action programs. And Gaertner argues that academic support

¹⁶⁰ Carnevale, Rose, and Strohl 2014, p. 201.

¹⁶¹ Kahlenberg Rebuttal, p. 2.

¹⁶² Thomas J. Kane, “Racial and Ethnic Preferences in College Admissions,” *Ohio St. Law Journal* 59, 1998, pp. 971–996 at p. 990 (“There may be other characteristics that are more highly correlated with race than income alone, such as family wealth or neighborhood poverty rates, that a college might use to construct a ‘race-blind’ measure for promoting racial diversity. However, since blacks and Hispanics are only 6.8 percent of the highest-scoring youth, it would be difficult to find a preference that would yield even a majority of black or Hispanic youth...even if high-scoring black or Hispanic youth were thirteen times more likely to meet some combination of wealth, neighborhood, and family income criteria than other youth, they would still represent less than half of the high-scoring youth meeting the criteria.”); 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. 14 (“Our simple simulations show that admissions policies like the Texas Top Ten Percent rule...alone are unlikely to increase the proportion of black and Hispanic and low-income students enrolled in highly-selective colleges...more sophisticated simulation models suggest that the Top Ten Percent rules would...lead to a 10% reduction in the proportion of black and Hispanic students attending highly-selective colleges and universities.”).

¹⁶³ Kahlenberg Rebuttal, p. 3; Expert Report of Richard D. Kahlenberg, *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College (Harvard Corporation)*, October 16, 2017 (“Kahlenberg Report”), pp. 12–13; Card Report, p. 101.

¹⁶⁴ Card Report, p. 101.

for low-income students should be the proper response, not ceasing to admit such students.”¹⁶⁵ I do not disagree that supporting low-income students is a worthwhile endeavor. In fact, the results from my admissions model suggest that Harvard gives an admissions “tip” to students who are flagged as disadvantaged, and to students whose parents work in lower-paying occupations. I do disagree with Mr. Kahlenberg’s characterization of Gaertner’s findings. In fact, Gaertner writes the following, contrary to Mr. Kahlenberg’s characterization:

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. This said, given additional time in college, disadvantaged admits’ graduation rates accelerate comparatively quickly [...] thereby narrowing the graduation gap. To sum, analysis of college outcomes for historical surrogates suggest college success for class-based admits is possible, but it is far from guaranteed[.]¹⁶⁶

177. Mr. Kahlenberg also objects to my characterization of Sigal Alon’s race-neutral simulations, which Mr. Kahlenberg cited in his initial report.¹⁶⁷ As I noted in my initial report, Alon’s race-neutral simulations do not consistently show that racial diversity would meet or exceed current levels. In her one simulation where the fraction of African-American and Hispanic admitted students surpasses that achieved by considering race, Alon finds that this diversity comes at the cost of a decline in academic selectivity.¹⁶⁸

178. Additionally, Mr. Kahlenberg argues that the literature’s focus on “efficiency” is misleading. Specifically, Mr. Kahlenberg conflates the concepts of “efficiency” and “administrative convenience,” and then argues that “convenience” is not the measure by which we should judge race-neutral alternatives.¹⁶⁹ Contrary to Mr. Kahlenberg’s argument, “efficiency” and “convenience” are two logically separate concepts that cannot be easily combined. In my report, and in the many papers we both cite, an “efficient” policy refers to an admissions policy that obtains the desired outcome (diversity) while minimizing the cost in other dimensions of the admitted class, such as academic

¹⁶⁵ Kahlenberg Rebuttal, p. 3.

¹⁶⁶ 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. 184–186.

¹⁶⁷ Kahlenberg Rebuttal, p. 4; Kahlenberg Report, p. 13.

¹⁶⁸ Card Report, p. 102; Sigal Alon, *Race, Class, and Affirmative Action* (New York, NY: Russell Sage Foundation, 2015), pp. 254–256.

¹⁶⁹ Kahlenberg Rebuttal, pp. 2–3.

preparedness or extracurricular excellence. The race-neutral alternatives I evaluate are inefficient not because they are “inconvenient,” but because they reduce Harvard’s ability to select applicants along other dimensions I understand it may value. For example, putting four times the weight on socioeconomic characteristics is a dramatic shift in policy that effectively reduces the relative weight that Harvard places on other characteristics it values, like extracurricular, athletic, and academic achievement. Similarly, a geographic quota or percent plan would severely constrain the extent to which Harvard can admit well-qualified candidates from exceptionally competitive areas.

179. Nevertheless, it is important to note that in addition to imposing efficiency costs (as this term is used in the literature, and in my report), race-neutral alternatives may also impose administrative and financial costs. Utilizing ZIP code, high school, or other geographic quotas, for example, could generate a massive increase in applications from less competitive areas or high schools, increasing the costs of Harvard’s admissions process. Further increases in financial aid and recruiting would also be costly. Mr. Kahlenberg dismisses these costs, but they may be of legitimate concern to a university, including Harvard.¹⁷⁰

180. Mr. Kahlenberg also argues that the finding in the literature regarding the difficulty of employing race-neutral alternatives at selective institutions is irrelevant because the schools studied “could have done more to promote diversity.”¹⁷¹ In other words, Mr. Kahlenberg appears to be arguing that analyses of prior attempts by selective universities to use race-neutral alternatives are inherently flawed, because they cannot rule out that those universities *could* have implemented more, or different, policies. Speculating that other selective universities “could have done more” shows a fundamental misunderstanding of the concept of empirical evidence. The existing literature on race-neutral alternatives provides such evidence by examining actual attempts by universities to implement race-neutral policies. Mr. Kahlenberg offers no factual support for the efficacy of the race-neutral policies he claims universities *could* have employed. Speculation is not the same as evidence.

181. Additionally, Mr. Kahlenberg suggests that one explanation for why race-neutral alternatives have been less effective in generating diversity at selective universities like U.C. Berkeley, UCLA, and Michigan is that these schools faced a “special disadvantage in recruiting minority students because they were prohibited by state law from using racial preferences, but their competitors were not.”¹⁷² Mr. Kahlenberg fails to note that Harvard would face the *exact same* “special disadvantage” if prohibited from using race as a factor in admissions. This fact renders the experience of these schools all the more relevant to assessing the potential effectiveness of race-

¹⁷⁰ Kahlenberg Rebuttal, pp. 24–25.

¹⁷¹ Kahlenberg Rebuttal, p. 5.

¹⁷² Kahlenberg Rebuttal, p. 5.

neutral alternatives at Harvard.

7.2. Mr. Kahlenberg’s new simulations confirm that the substitution of race-neutral alternatives for Harvard’s race-conscious admissions process would change the characteristics of the class and compromise its quality

182. Mr. Kahlenberg’s rebuttal simulates Harvard’s admitted class under two new race-neutral alternatives that he claims address several shortcomings of the simulations I modeled in my first report. In this section, I first summarize the criticisms that Mr. Kahlenberg offers of my simulations, and then discuss the findings of his new simulations.

183. As I show below, even if I accept Mr. Kahlenberg’s new simulations, they support the main findings of my first report. Specifically, both of his new simulations show that race-neutral alternatives substantially alter the characteristics of the admitted class and diminish its quality, as measured by Harvard profile ratings and other indicia. Moreover, although Mr. Kahlenberg’s new simulations increase the fraction of Asian-American and Hispanic admitted students, they still result in a pool of admitted African-American students that is substantially smaller than the current pool. This pattern is not surprising, and is fully consistent with the conclusions from the broader academic literature that race-neutral alternatives cannot achieve diversity at selective institutions without a meaningful cost to quality.

7.2.1. Mr. Kahlenberg’s criticisms of my simulations

184. Mr. Kahlenberg criticizes my simulations in five primary ways. First, Mr. Kahlenberg criticizes the way in which I boost the probability of admission for low-SES students in my simulations, and offers his own variation on my methodology.¹⁷³ In my simulations, I simulate giving a “low-SES boost” to applicants who exhibit the following characteristics: disadvantaged, requested a fee waiver, first generation college student, neighborhood median income less than or equal to \$65,000. An applicant who meets all four criteria receives the full low-SES boost, while an applicant who meets only two criteria receives a boost equal to one-half the full boost. I start by setting the value of the full boost at two additional points to an applicant’s admissions index, and then scale this boost up across my various simulations.¹⁷⁴ Mr. Kahlenberg suggests that on the one hand, the set of socioeconomic criteria I target in my simulations is too limited. On the other hand, he argues that labeling applicants with median neighborhood below \$65,000 as low-SES is too generous—he thinks the threshold ought to be lower.

¹⁷³ Kahlenberg Rebuttal, pp. 31–32.

¹⁷⁴ The admissions index is the input into the logit function that determines an applicant’s probability of admission.

185. To address these alleged deficiencies, he proposes a new weighting scheme. He starts by constructing indices that measure neighborhood and high school SES. The indices give equal weight to three factors: parental income, parental education, and percentage of families speaking a language other than English at home.¹⁷⁵ Then, just as in my simulations, Mr. Kahlenberg gives applicants with certain socioeconomic characteristics a low-SES boost by adding a value to their admissions index. The value of the boost is equal to 1.6 multiplied by the number of low-SES criteria an applicant meets, where the criteria are: disadvantaged, requested a fee waiver, first generation college student, applicant obtains a neighborhood SES index score in the bottom third of the distribution, and applicant obtains a high school SES index score in the bottom third of the distribution.¹⁷⁶

186. Second, Mr. Kahlenberg argues that it is important to simulate the effect of eliminating Early Action by turning off the preference Harvard accords such applicants because he argues that Early Action “disproportionately benefits white and wealthy students.”¹⁷⁷ He criticizes me for not doing so in my simulations.¹⁷⁸ Mr. Kahlenberg’s proposal is problematic, however. The large, positive effect of applying Early Action on admission is a composite of many unobservable factors that distinguish those who apply early from those who do not.

187. Early Action applicants may be better qualified in unobservable dimensions. In addition, as Prof. Arcidiacono explains, “[g]iving preferences for early action is consistent with the yield rate being higher for early action applicants.”¹⁷⁹ The higher yield rate for Early Applicants may reflect many applicant characteristics, including their stronger interest in Harvard, better fit with a particular department or area of study, or greater affinity for Harvard’s extracurricular offerings. Thus, Mr. Kahlenberg’s position that preferences for Early Action applicants primarily reflect a reward for being “white and wealthy” is at odds with that of Prof. Arcidiacono, who designed Mr. Kahlenberg’s simulations, and who acknowledges that the preference for Early Action is consistent with traits Harvard may value. Furthermore, my initial report demonstrated that when Harvard restored Early Action for the class of 2016 after having eliminated it for several years, this change was *not* associated with a decline in the fraction of African-American, Hispanic, and Other (non-Asian) minority race (“AHO”) applicants, admitted students, or matriculants.¹⁸⁰ If anything, matriculation

¹⁷⁵ Kahlenberg Rebuttal, pp. 30–31.

¹⁷⁶ Kahlenberg Rebuttal, pp. 30–31; see also SFFA-HARVARD 0002346_simulation6.do and SFFA-HARVARD 0002347_simulation7.do in Mr. Kahlenberg’s backup.

¹⁷⁷ Kahlenberg Rebuttal, p. 18.

¹⁷⁸ Kahlenberg Rebuttal, pp. 18–19.

¹⁷⁹ Arcidiacono Rebuttal, p. 3, footnote 1.

¹⁸⁰ Card Report, pp. 147–150.

rates were higher for students of all races under the Early Action regime, particularly for AHO admitted students.¹⁸¹ This undermines the idea that eliminating Early Action would be a strong lever for generating diversity.

188. Third, Mr. Kahlenberg repeatedly criticizes me for removing preferences for recruited athletes in my simulations.¹⁸² That is surprising because four of his five simulations do the same. Indeed, SFFA did not propose this policy in its Complaint—it was introduced by Mr. Kahlenberg himself in his initial report.¹⁸³ I removed preferences for athletes in my featured simulations in order to be conservative, employing more of his proposed race-neutral tools, rather than fewer. While his preferred simulation (Simulation 4) excludes this policy, Mr. Kahlenberg’s only reason for restoring the athletic preference is that “removing athletic preferences in connection with race neutral alternatives is sometimes perceived as radical.”¹⁸⁴ It is unclear why Mr. Kahlenberg would introduce and feature a policy, only to disparage it so severely—but regardless, my initial findings are robust to restoring the preference for recruited athletes (see the discussion of Exhibit 26 below).

189. Fourth, Mr. Kahlenberg makes factually incorrect statements about my simulations. He states, for example, that my initial report “does *not* simulate the racial impact of eliminating ... preferences for the children of alumni, donors, faculty and staff, and those admitted through the Z-list.”¹⁸⁵ But the only practice that Mr. Kahlenberg identifies in that statement that I do not simulate is removing consideration of whether an applicant’s parents could donate to Harvard. The reason I do not, as I explained, is because I do not have data that identifies these applicants—and neither does Mr. Kahlenberg, so he cannot simulate this effect, either.

190. Fifth, Mr. Kahlenberg makes the broad critique of my initial analysis that, because any given race-neutral alternative he proposed in his initial report is unlikely to be effective on its own,

¹⁸¹ Card Report, pp. 149–150.

¹⁸² Kahlenberg Rebuttal, pp. 11–12, 32.

¹⁸³ Kahlenberg Report, pp. 45–46.

¹⁸⁴ Kahlenberg Report, p. 46.

¹⁸⁵ Kahlenberg Rebuttal, p. 11. Mr. Kahlenberg also cites a paper published in his book contending that legacy preferences are not associated with higher alumni giving (Kahlenberg Rebuttal, p. 12; Kahlenberg Report, p. 33). This paper uses aggregated data at the college level to examine the determinants of mean alumni giving, rather than the preferred approach of examining the donation decisions of individual alumni with different potential incentives to give. Moreover, it relies on limited proxies for alumni characteristics, such as mean Pell grants per currently enrolled student as a measure of alumni wealth. In my opinion the empirical analysis in this paper is very weak and is uninformative about the reasons for alumni giving.

proper analysis must consider all of them in conjunction.¹⁸⁶ On this point, I agree with Mr. Kahlenberg, which is why I conducted just such a combined analysis in my initial report. It is important to evaluate the potential effects of multiple race-neutral alternatives used in conjunction. In fact, I explained this challenge in my first report, and included results for a simulation that combined the following race-neutral alternatives:

- Eliminated preferences for lineage applicants, recruited athletes, children of Harvard faculty and staff, and applicants on the Dean and Director’s interest lists
- Increased the preference given to low-SES applicants
- Admitted students equally across College Board clusters (the place-based policy simulated in Mr. Kahlenberg’s initial report)
- Doubled the number of disadvantaged applicants Harvard was able to attract (assuming no change to the quality of disadvantaged applicants)

191. In that analysis, I found that, even taken together, these policies were unlikely to generate both diversity and class quality.¹⁸⁷ Tellingly, Mr. Kahlenberg does not comment on the above simulation, even though it directly addresses his concern.

7.2.2. The results of Mr. Kahlenberg’s new simulations support the conclusions of my first report

192. Mr. Kahlenberg puts forward two additional simulations in his rebuttal. Mr. Kahlenberg’s Simulation 6 retains the same sample and regression model as my own. As in my simulations, he eliminates consideration of race, lineage 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. As noted above, he makes three main changes to my simulations. He does not remove

¹⁸⁶ Kahlenberg Rebuttal, p. 1 (“These strategies, when used in tandem with one another, can produce the educational benefits of diversity[.]”), p. 10 (“[M]y opening report never suggested that increasing financial aid is a stand-alone strategy that would automatically increase racial diversity.”), p. 12 (“[T]he elimination of preferences that tend to favor wealthy and white students was not meant to be a stand-alone race-neutral alternative[.]”), p. 18 (“[M]y contention is not that community college transfers alone is the answer; it is that increasing the number of community college students at Harvard is one piece of a larger solution[.]”).

¹⁸⁷ Card Report, pp. 137–138, Exhibit 53.

consideration of recruited-athlete status, he eliminates the preference associated with applying Early Action, and he gives applicants with certain socioeconomic characteristics a low-SES boost by adding a value to their admissions index that reflects a slightly different set of low-SES criteria than my model, as described above.¹⁸⁸ Mr. Kahlenberg's Simulation 7 is the same as Simulation 6, except that it restores consideration of Early Action status.

193. Exhibit 26 presents the results of Mr. Kahlenberg's Simulation 6. Starting first with its effect on diversity, we see that Simulation 6 generates a substantial increase in the fraction of Hispanic or Other applicants in the admitted class. The fraction of admitted students who are African-American, however, remains 30% lower than in the actual class. His Simulation 7 performs similarly.

194. In his initial report, Mr. Kahlenberg reported the average profile ratings associated with each of his simulated classes.¹⁸⁹ Notably, he excludes those outcomes when he reports results for Simulations 6 and 7.¹⁹⁰ Fortunately, Prof. Arcidiacono's code for Mr. Kahlenberg's simulations computes and records not only information on ratings, but also all of the metrics I used in my own report to evaluate how different policies impact class characteristics. Mr. Kahlenberg chooses not to report the findings from Prof. Arcidiacono's output, but I report them in full in Exhibit 26.

195. When discussing his new simulations, Mr. Kahlenberg uses my "4x low-SES boost" simulation as a benchmark. I follow suit in this section. It is worth noting that in his rebuttal, Mr. Kahlenberg argues that this simulation represents a "viable" race-neutral alternative for Harvard, despite the fact that the simulation results in a decline in the fraction of students with top profile ratings, and a fraction of African-American admitted students that is about 30 percent lower than that of the current class (among other changes to class characteristics).¹⁹¹ His arguments do not change my conclusion that this race-neutral alternative produces a class that is different from the current class in dimensions I understand Harvard cares about; but I use the "4x low-SES boost" simulation as a benchmark to be consistent with Mr. Kahlenberg.

196. First, although Mr. Kahlenberg's new simulations generate a larger fraction of African-American and Hispanic admitted students, as compared to my 4x low-SES simulation, his simulations (like mine) produce a class that has a full 30% fewer African-American students than the actual admitted class—a dramatic drop. Mr. Kahlenberg's simulations also result in a class with slightly lower average SAT and ACT scores, as compared to my simulation. Because he retains a

¹⁸⁸ Kahlenberg Rebuttal, pp. 29–32.

¹⁸⁹ Kahlenberg Report, Appendix C.

¹⁹⁰ Kahlenberg Rebuttal, pp. 33, Appendix A.

¹⁹¹ Kahlenberg Rebuttal, p. 21 ("Instead, in this section, I show that (1) Card incorrectly concludes that Arcidiacono Simulation 4 and Card's 4x are not viable race neutral alternatives; and (2) a new simulation from Card's model (Simulation 6) demonstrates viable race-neutral alternatives.").

preference for athletic recruits, his simulated classes do have better athletic ratings than in my 4x simulation. Importantly, Mr. Kahlenberg's new simulations reduce the fraction of the admitted class with academic, personal, and extracurricular ratings of 1 or 2. These reductions are larger than in my benchmark simulation.

197. In sum, Mr. Kahlenberg's new simulations are no better at increasing the fraction of African-American students in the class (relative to a baseline in which Harvard does not consider race) than my simulations, and come at a higher cost to other factors that Harvard values in the admissions process, including academic excellence. In other words, Mr. Kahlenberg's new simulations simply reinforce the point made repeatedly in my initial report and in the academic literature: it is extremely difficult to generate diversity using race-neutral alternatives without inflicting costs in other dimensions a university may value.

Exhibit 26

Kahlenberg's Simulation 6 and 7: Impact on class characteristics

Outcome Measures	Predicted Class Without Consideration of Race and Factors that Allegedly Advantage White Applicants						
	Actual Admitted Class [A]	Card's Simulation (4x SES Boost)		Kahlenberg's Simulation 6		Kahlenberg's Simulation 7	
		Predicted Value [B]	% Change $\frac{[B]-[A]}{[A]}$	Predicted Value [C]	% Change $\frac{[C]-[A]}{[A]}$	Predicted Value [D]	% Change $\frac{[D]-[A]}{[A]}$
Race							
1. White	676	589	-13%	541	-20%	561	-17%
2. Asian-American	402	508	+26%	523	+30%	521	+30%
3. Hispanic or Other	233	293	+26%	330	+42%	313	+34%
4. African-American	234	163	-30%	164	-30%	160	-32%
5. Race Missing	134	127	-6%	121	-10%	123	-8%
Academic							
6. Average Composite SAT Score	2244	2189	-2%	2173	-3%	2180	-3%
7. Average Composite ACT Score	33.1	32.7	-1%	32.5	-2%	32.5	-2%
8. Average Converted GPA	77.0	77.1	+0.1%	77.0	+0.02%	77.0	+0.02%
9. Average Academic Index	228	225	-1%	225	-1%	225	-1%
Fraction with Profile Rating of 1 or 2							
10. Academic	76%	66%	-13%	61%	-19%	63%	-17%
11. Extracurricular	62%	57%	-9%	54%	-13%	55%	-12%
12. Personal	71%	64%	-11%	62%	-13%	63%	-11%
13. Athletic	27%	18%	-33%	20%	-26%	21%	-22%
Applicant Characteristics							
14. Number of Lineage Students	259	86	-67%	61	-76%	81	-69%
15. Number of Double Lineage Students	72	19	-73%	13	-81%	18	-75%
16. Number of Recruited Athletes	180	88	-51%	144	-20%	159	-11%
17. Number of Children of Harvard Faculty and Staff	44	17	-61%	12	-74%	16	-64%
18. Number of Students on Dean's and Director's Interest Lists	Redacted						
19. Number of Female Students	839	851	+1%	858	+2%	851	+1%
Concentration							
20. Social Sciences	25%	24%	-5%	24%	-4%	24%	-2%
21. Humanities	15%	13%	-9%	12%	-15%	12%	-14%
22. Biological Sciences	21%	23%	+11%	24%	+12%	24%	+12%
23. Physical Science	7%	8%	+6%	7%	-5%	7%	-5%
24. Engineering	13%	13%	+5%	14%	+14%	14%	+8%
25. Computer Science	6%	6%	-7%	6%	-4%	6%	-6%
26. Mathematics	6%	7%	+3%	6%	+1%	6%	+0.5%
27. Unspecified	7%	6%	-9%	6%	-6%	7%	-3%
Geography							
28. Number Rural	59	87	+48%	87	+47%	82	+39%
29. Number in Northeast	694	604	-13%	615	-11%	630	-9%
30. Number in Midwest	207	217	+5%	164	-21%	170	-18%
31. Number in South	379	407	+7%	392	+3%	391	+3%
32. Number in West	399	451	+13%	509	+27%	488	+22%

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

Note: My simulation (“Card’s Simulation (4x SES Boost)”) consists of applicants to the class of 2019 in Prof. Arcidiacono’s expanded sample including athletes, who are in my preferred year-by-year regression model from my affirmative report. The 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 admissions index. The value is equal to 2 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. Kahlenberg’s simulation 6 retains the same sample and regression model from my simulation. Simulation 6 eliminates consideration of the same characteristics as my simulation except for recruited-athlete status. Simulation 6 also eliminates consideration of Early Action status. Applicants with certain socioeconomic characteristics are given a low-SES boost by adding a value to their admissions index. The value is equal to 1.6 multiplied by the number of characteristics an applicant displays out of the following: disadvantaged, requested a fee waiver, first generation college student, applicant obtains a neighborhood SES index score in the bottom third of the distribution, applicant obtains a high school SES index score in the bottom third of the distribution. The neighborhood and high school SES indices are constructed by equally-weighting three standardized factors: parental income, parental education, and percentage of families speaking a language other than English at home. Kahlenberg’s simulation 7 is the same as simulation 6 except that it retains consideration of Early Action status.

7.3. Other race-neutral alternatives are unlikely to generate diversity without changing class characteristics and compromising class quality

198. Mr. Kahlenberg also critiques my analyses of the role that different approaches to financial aid, recruiting, transfer admissions, and deferred admission could play in increasing diversity at Harvard. Additionally, he lays out a vague suggestion for how Harvard could allegedly use place-based admissions policies to increase diversity. I address each of these critiques below.

7.3.1. Increasing financial aid

199. Mr. Kahlenberg argues that Harvard could offer more generous financial aid and that doing so could increase the diversity of its admitted class.¹⁹² I evaluated this claim in my initial report by looking at how historical expansions in financial aid influenced the composition of applicants, admitted students, and matriculants. I focused on Harvard’s most recent expansion: starting with the class of 2016, Harvard expanded its threshold for attendance at zero personal cost from \$60,000 to \$65,000. In my initial report, I showed that this expansion was not associated with an increase in AHO applicants, admitted students, or matriculants.¹⁹³ My report also explained why this might not be surprising: even with a threshold of \$60,000 for attendance at zero personal cost, Harvard was already free for the vast majority of Hispanic and African-American households.¹⁹⁴ I took this as evidence that future expansions in financial aid were unlikely to be a powerful lever for increasing

¹⁹² Kahlenberg Rebuttal, pp. 9–10.

¹⁹³ Card Report, pp. 142–145.

¹⁹⁴ Card Report, p. 140.

racial diversity.

200. In his rebuttal, Mr. Kahlenberg complains that I should not treat this expansion as an increase in financial aid, because it was accompanied by a reduction in aid to families making between \$150,000 and \$180,000.¹⁹⁵ This complaint is misplaced, in my view. The key policy change in question—raising the threshold for attendance at zero personal cost—is targeted at applicants at the *lower* end of the income distribution, where both Mr. Kahlenberg and I would expect to see a response from disadvantaged applicants. Thus, I maintain that looking at the most recent expansion in the threshold for zero-parental contribution is a helpful and informative exercise for understanding how future increases in aid might affect the pool of applicants, admitted students, and matriculants.

201. It is also worth noting that elsewhere in his report, Mr. Kahlenberg implicitly admits that financial aid is already exceptionally generous at Harvard for both disadvantaged and middle-class applicants. In evaluating my simulations, he writes “[t]he problem with Card’s \$65,000 threshold [for identifying low-SES applicants] is that it includes middle-class as well as economically disadvantaged neighborhoods. (In 2016, the median household income was \$57,617.)”¹⁹⁶ In other words, Mr. Kahlenberg considers families making \$65,000 middle class. By Mr. Kahlenberg’s standard, Harvard already requires no financial contribution from applicants from disadvantaged neighborhoods, as well as many middle-class ones.

7.3.2. *Increasing recruiting*

202. Mr. Kahlenberg dismisses my concern that doubling the pool of disadvantaged applicants to Harvard may be challenging, and that doing so would likely have an impact on the average quality of disadvantaged applicants.¹⁹⁷ He suggests that there is a large pool of qualified candidates who do not apply to Harvard, noting that “82% of American high schools have not a single applicant to Harvard, one of the world’s best known colleges.”¹⁹⁸ As the statement itself implies, this is probably not because these students are unaware of Harvard. It is more likely that these students are either academically unprepared for Harvard, have personal reasons for not applying (e.g., because they prefer to attend college in a different part of the country), lack information on the application process or the availability of financial aid, or are concerned about their own fit with

¹⁹⁵ Kahlenberg Rebuttal, p. 10.

¹⁹⁶ Kahlenberg Rebuttal, pp. 31–32.

¹⁹⁷ Kahlenberg Rebuttal, pp. 15–17.

¹⁹⁸ Kahlenberg Rebuttal, p. 16.

Harvard in terms of academic and extracurricular interests. My reading of the available materials in this case is that Harvard is aware of the potential information gaps that face some students and that Harvard actively tries to provide this information through extensive recruiting visits, social media campaigns, targeted mailings, and engagement with local public schools.¹⁹⁹ As I detailed in my previous report, Harvard also purchases extensive search lists from testing agencies, and conducts a variety of forms of direct outreach by staff and students involved in the wide array of recruiting programs I described in my initial report.²⁰⁰

203. Second, Mr. Kahlenberg cites the work of economists Caroline Hoxby and Christopher Avery to support his point that there is a pool of talented, low-income applicants who do not apply to selective colleges, despite being qualified for admission.²⁰¹ While I agree with those authors that there are likely talented students in disadvantaged circumstances who currently do not apply to selective schools like Harvard, as I explained in my report, those same authors indicate that many of these students are “isolated from other high achievers, both in terms of geography and in terms of the high schools they attend,” rendering them particularly difficult to reach.²⁰² As detailed at length in my initial report, Harvard already engages in extensive recruiting, and Harvard already employs the very interventions suggested by Hoxby and Avery in their paper.²⁰³

204. Mr. Kahlenberg also cites an academic study suggesting that there are about 5,160 Hispanic students and 2,580 African-American Pell Grant recipients “who have test scores comparable to those of students at selective colleges but who do not now attend such institutions.”²⁰⁴ He takes this as evidence that Harvard could easily double its pool of disadvantaged applicants without any impact on quality. If anything, I think these figures underscore how challenging expanding the pool of qualified disadvantaged candidates can be. Between 2014 and 2019, Harvard flagged several thousand students each year as being disadvantaged (over 4,700 in 2019).²⁰⁵ By comparison, the authors of this study identify fewer than 8,000 potential applicants, an unknown number of whom may have already applied to Harvard and been rejected. Further, test scores are the

¹⁹⁹ Card Report, pp. 120–122.

²⁰⁰ Card Report, pp. 120–122. These programs include the Undergraduate Minority Recruitment Program, the Harvard First Generation Program, the Harvard College Connection, Project Teach, and the Cambridge-Harvard Summer Academy.

²⁰¹ Kahlenberg Rebuttal, p. 16.

²⁰² Card Report, p. 122, footnote 198.

²⁰³ Card Report, pp. 120–122.

²⁰⁴ Kahlenberg Rebuttal, pp. 16–17.

²⁰⁵ See workpaper.

only metric by which the authors measure quality, which is not particularly helpful for understanding how well these potential applicants would stack up against current candidates for admission to Harvard.

7.3.3. Increasing transfer admissions

205. Mr. Kahlenberg also argues that Harvard could increase diversity by increasing the number of transfer applicants Harvard admits from community colleges.²⁰⁶ In my first report, I showed that current transfer applicants are no more diverse than Harvard’s regular applicant pool, and pointed out that admitting a large number of transfer students would require restricting the size of the regularly-admitted freshman class, as so few students drop out of Harvard.²⁰⁷ In his rebuttal, Mr. Kahlenberg argues that it is irrelevant to analyze the composition of current transfer students, since Harvard only accepted two such students to the classes of 2014 to 2019.²⁰⁸ Mr. Kahlenberg seems to have missed the point: I did not analyze the racial composition of current transfer students. I analyzed the composition of the pool of transfer applicants. To reiterate: the pool of students who apply to transfer to Harvard is no more diverse than the pool of applicants who apply to the freshman class. As a result, I would not expect an increase in the number of transfer students Harvard admitted to have an impact on racial diversity.

7.3.4. Eliminating deferred admission

206. In his rebuttal, Mr. Kahlenberg states that my simulations do not address his suggestion that Harvard could increase diversity by ending the practice of deferred admission.²⁰⁹ This is factually inaccurate. As stated in my initial report, I simulate the effect of eliminating deferred admission (the “Z-list”) by using a model that fills all seats in the entering class with students who apply in a given year, based on their characteristics.²¹⁰ All of my simulations eliminate the practice of deferred admission.

²⁰⁶ Kahlenberg Rebuttal, pp. 17–18.

²⁰⁷ Card Report, p. 119.

²⁰⁸ Kahlenberg Rebuttal, p. 17.

²⁰⁹ Kahlenberg Rebuttal, p. 11.

²¹⁰ Card Report, p. 104.

7.3.5. Place-based admissions policies

207. Mr. Kahlenberg’s initial report advocated for place-based policies, such as admitting top students by high school (e.g., the Texas Top 10 Percent Plan) or by ZIP code.²¹¹ He particularly emphasizes the latter. Now, acknowledging my point that it is not possible for Harvard to admit top students from every U.S. high school or ZIP code, Mr. Kahlenberg pivots from that style of place-based policy in his rebuttal. Instead, he suggests that Harvard “could easily seek excellence and socio-geographic diversity by enrolling top students from all of the College Board’s 33 ‘Educational Neighborhood Clusters,’ as we model, or some variation of Harvard’s choosing.”²¹² In a footnote, he then suggests that Harvard could admit top students across buckets of ZIP codes in lieu of College Board clusters.

208. First, Harvard already “seek[s] excellence and socio-geographic diversity,” and Harvard already “enroll[s] top students from all of College Board’s 33 ‘Educational Clusters.’”²¹³ Aside from Mr. Kahlenberg’s suggestion that Harvard consider only race-neutral criteria in its holistic admissions process, I fail to see how this vague proposal differs from Harvard’s current practices.

209. Further, as I showed in my initial report, the policy Mr. Kahlenberg initially proposed (which admitted an equal number of applicants across clusters) results in a class with lower personal, academic, extracurricular, and athletic ratings, as compared to the status quo.²¹⁴ One reason for this change is that imposing geographic quotas would necessarily limit Harvard’s ability to accept additional students from the most competitive geographic slates. Simply substituting buckets of ZIP codes for College Board clusters—which are themselves collections of census tracts—seems no more promising than using clusters themselves.

7.4. Conclusion

210. In this section, I addressed Mr. Kahlenberg’s criticisms of my analysis of race-neutral alternatives, and demonstrated the robustness of my findings. I maintain the position put forth in my first report: even considered in combination, the race-neutral alternatives put forward by Mr. Kahlenberg are blunt and ineffective instruments for generating a diverse class, as they limit

²¹¹ Kahlenberg Report, pp. 36–39.

²¹² Kahlenberg Rebuttal, pp 14–15.

²¹³ See workpaper.

²¹⁴ Card Report, pp. 151–153.

Harvard's ability to select applicants based on other characteristics that it values. The policies I analyzed either did little to generate a class comparable in diversity to the current class, or did so only by significantly changing class characteristics and compromising class quality. Whether these policies generate a class that meets Harvard's educational needs is beyond the scope of my opinion,²¹⁵ but the empirical evidence is clear: using the race-neutral alternatives proposed by Mr. Kahlenberg to generate diversity comes at a cost.



David Card

March 15, 2018

²¹⁵ I understand that a committee led by Dean Michael Smith will address the question of whether or not these race-neutral policies would generate an admitted class that meets Harvard's educational needs.

8. APPENDIX A

8.1. Documents Relied Upon

Expert Reports

Expert Report of David Card, Ph.D., *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College (Harvard Corporation)*, December 15, 2017.

Expert Report of Peter S. Arcidiacono and backup materials, *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College (Harvard Corporation)*, October 16, 2017.

Rebuttal Expert Report of Peter S. Arcidiacono and backup materials, *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College (Harvard Corporation)*, January 30, 2018.

Expert Report of Richard D. Kahlenberg and backup materials, *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College (Harvard Corporation)*, October 16, 2017.

Rebuttal Expert Report of Richard D. Kahlenberg and backup materials, *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College (Harvard Corporation)*, January 30, 2018.

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HARV00001224; HARV00001322; Lists of database fields produced.

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David Zimmerman, “Regression Toward Mediocrity in Economic Stature,” *The American Economic Review* 82(3), 1992, pp. 409–429.

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James J. Heckman, “Sample Selection Bias as a Specification Error,” *Econometrica* 47(1), 1979, pp. 153–161.

Peter Arcidiacono et al., “Recovering Ex Ante Returns and Preferences for Occupations using Subjective Expectations Data,” NBER Working Paper #20626, October 2014.

Peter Arcidiacono, Jane Cooley, and Andrew Hussey, “The Economic Returns to an MBA,” *International Economic Review* 49(3), 2008, pp. 873–899.

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.

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HARV00001851 – 56, “Applicants, Admits, and Matriculants – Old Methodology NLNA”

HARV00004683 – 89, COFHE Admissions Statistics, Class Entering 2013

HARV00005106, “Ethnicity Backgrounds – Classes of 2014 – 2017”

HARV00013561 – 65, Sarasota Presentation, “KLW - Sarasota Presentation”

HARV00018164 – 76, “Discussion Guide to the 2012 Casebook”

HARV00022645, Email from Katey Stone to Grace Cheng and Nathan Fry, “FW: Harvard Women’s Ice Hockey,” November 30, 2012

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9. APPENDIX B: OTHER TECHNICAL CRITIQUES OF PROF. ARCIDIACONO'S REPORT

9.1. Appendix B.1 Constructing categories for parental occupations

211. Parent occupations are stored in a field in the NEVO database. This field uses two distinct sets of occupational codes, and the prevalence of either set of codes changes over time, most notably between 2014 and 2015, when the second set of codes is first introduced. I harmonize the two sets of codes by mapping them to the Bureau of Labor Statistics' occupational categories, which are standard occupational categories used in the labor economics literature.²¹⁶ Prof. Arcidiacono also takes issue with the way I aggregate occupational categories to create indicator variables in my regression. His critique is vague: it is limited to a footnote that states my translation is "incorrect" and is supported only by one example he disagrees with.

212. To harmonize the two sets of occupational codes Harvard used within each year, I create a mapping between these codes and the Bureau of Labor Statistics' occupational codes. This also allows me to aggregate occupations that the BLS considers similar into "BLS major groups." I combine some of these groups in order to create a meaningful but parsimonious set of occupational variables. I also split some "major groups" to create categories that more accurately reflect parents' socioeconomic status, e.g., I split doctors from nurses, who would otherwise remain together in the "healthcare practitioners" category. The complete mapping is shown at the end of this section in Exhibit 28.

213. Prof. Arcidiacono critiques my mapping by pointing to one example of an applicant whom he believes was miscoded. He writes that for this applicant: "Handwritten notes [on the applicant's summary sheet] show the occupations as 'caregiver' and 'newspaper deliveryman'. Yet Professor Card's classification scheme results in this applicant being coded as 'Skilled Trades Incl. Construction.'"²¹⁷

214. First, it is important to note that handwritten notes on summary sheets are not available in Harvard's data, and that Harvard only produced summary sheets for several hundred out of more than a hundred thousand applicants. My analysis of occupations is based on the most comprehensive

²¹⁶ Daron Acemoglu and David Autor, "Skills, Tasks and Technologies: Implications for Employment and Earnings," in *Handbook of Labor Economics, Volume 4A*, ed. Orley Ashenfelter and David Card (San Diego, CA: North-Holland, 2011), pp. 1043–1171 at pp. 1048–1049, p. 1164; IPUMS USA, "ACS Occupation Codes (OCC)," available at <https://usa.ipums.org/usa/volii/c2ssoccup.shtml>, accessed February 19, 2018; Alan S. Blinder and Alan B. Krueger, "Alternative Measures of Offshorability: A Survey Approach," *Journal of Labor Economics* 31(2), 2013, pp. S97–S128 at pp. S100–S101; David H. Autor and Michael J. Handel, "Putting Tasks to the Test: Human Capital, Job Tasks, and Wages," *Journal of Labor Economics* 31(2), 2013, pp. S59–S96 at p. S71.

²¹⁷ Arcidiacono Rebuttal, p. 32, footnote 17.

data at hand—the variables coded in Harvard’s database.

215. In the example at hand, Harvard’s data lists the applicant’s parents as “laborers, unskilled.” I mapped “laborers, unskilled” into the BLS category that covers construction workers, as laborers traditionally worked in this field. Because construction is a mix of unskilled laborers and more skilled tradespeople, I also combined construction with the BLS group for skilled trades. This yields an occupational category that consists of unskilled laborers, construction workers, and tradespeople. While this scheme may not capture the granularity of “newspaper deliveryman,” it does capture something sensible and pertinent about status and class.

216. Because the data are somewhat complex and require harmonization, Prof. Arcidiacono would have us toss this information out entirely. I disagree. I use the sensible mapping reported below to create parsimonious but meaningful occupational categories that reflect information salient to admissions officers. I then include these in my year-by-year model.

217. While my preferred categorization is reliable, my results are robust to alternative occupational categorizations that are reasonable and that fully address Prof. Arcidiacono’s critiques. I re-estimate my model using the following changes to occupational categories, separately and at the same time:

- Creating a “low skill” group that consists of parents coded as “laborer, unskilled” and “low skill.” In my preferred classification, parents coded as “laborer, unskilled” were grouped with construction workers and skilled tradesmen.
- Combining parents coded as homemakers, self-employed, other, and unemployed into one category.

218. My results are robust to this change. Exhibit 27 reports the marginal effect of being Asian-American for these models. The effect of being Asian-American remains insignificant (on average and in each of the six years).

My results are robust to changes in occupational classifications

**Average Marginal Effect of Asian-American Ethnicity
(Not Statistically Significant)**

Class	Categorizing "Laborer (Unskilled)" as low skill	Creating new category for self- employed, homemaker, unemployed, and other	Both modifications
1. 2014	-0.39	-0.39	-0.39
2. 2015	-0.06	-0.04	-0.05
3. 2016	0.09	0.07	0.06
4. 2017	0.11	0.11	0.11
5. 2018	-0.43	-0.42	-0.43
6. 2019	0.31	0.32	0.29
Overall	-0.06	-0.05	-0.06

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 previously defined expanded sample. * indicates significance at the 5% level. Marginal effects are reported as percentage point values.

Construction of occupational categories

Card Category	BLS Major or Minor Group	BLS, "99-XXXX", and "00-XXXX" Codes	"2010-XX" Codes
0 Other	-	Includes 99-0004, Undecided; 99-0002 and 00-0003, Retired; 99-0003 and 00-0004, Other; or missing	-
1 Homemaker	-	Includes 00-0001, Homemaker	Includes 2010-21, Homemaker (full-time)
2 Unemployed	-	Includes 99-0001 and 00-0002, Unemployed; 99-0005, Disabled	-
3 Skilled Trades Incl. Construction and Extraction	47, 49, 51	Includes 47, Construction and Extraction; 49, Installation, Maintenance and Repair; 51, Production	Includes 2010-42, Skilled Trades; 2010-44, Semi-Skilled Worker; 2010-43, Laborer (unskilled)
4 Low Skill Occupations	35, 53, 37, 45, 31, 39	Includes 35, Food Preparation and Serving; 53, Transportation and Material Moving; 37, Building and Grounds Cleaning and Maintenance; 45, Farming, Fishing and Forestry; 31, Healthcare Support; 39, Personal Care and Service	Includes 2010-15, Conservationist or Forester
5 Self-Employed	-		Includes 2010-07, Business Owner or Proprietor

Card Category	BLS Major or Minor Group	BLS, "99-XXXX", and "00-XXXX" Codes	"2010-XX" Codes
6 Business Executive (management, administrator)	11-1, 11-2, 11-3	Includes 11-1, Top Executives; 11-2 Advertising, Marketing, Promotions, Public Relations, and Sales Managers; 11-3, Operations Specialties Managers	Includes 2010-06, Business Executive (management, administrator); 2010-20, Foreign Service Worker (including diplomat); 2010-32, Policymaker/Government
7 Other Management Occupations (Excl. Business Execs)	11-9	Includes 11-9, Other Management Occupations	Includes 2010-34, School Principal or Superintendent; 2010-12, College Administrator or Staff
8 Business and Financial Operations Occupations	13	Includes 13, Business and Financial Operations	Includes 2010-01, Accountant or Actuary
9 Computer and Mathematical Occupations	15	Includes 15, Computer and Mathematical	Includes 2010-14, Computer Programmer or Analyst
10 Architecture and Engineering Occupations	17	Includes 17, Architecture and Engineering	Includes 2010-18, Engineer; 2010-03, Architect or Urban Planner
11 Life, Physical, and Social Science Occupations	19	Includes 19, Life, Physical, and Social Science	Includes 2010-35, Scientific Researcher; 2010-11, Clinical Psychologist
12 Counselors, Social Workers, and Other Community and Social Service Specialists	21	Includes 21, Community and Social Services Occupations	Includes 2010-09, Clergy (minister, priest); 2010-10, Clergy (other religious); 2010-33, School Counselor; 2010-36, Social, Welfare, or Recreation Worker
13 Lawyers, Judges, and Related Workers	23-1	Includes 23-1, Lawyers, Judges, and Related Workers	Includes 2010-25, Lawyer (attorney) or Judge
14 Postsecondary Teachers	25-1	Includes 25-1, Postsecondary Teachers	Includes 2010-13, College Teacher
15 Pre-K through Grade 12 Educational Instruction and Library Occupations	25-2, 25-3, 25-4, 25-9	Includes 25-2, Preschool, Primary, Secondary, and Special Education School Teachers; 25-3, Other Teachers and Instructors; 25-4, Librarians, Curators, and Archivists; 25-9, Other Education, Training, and Library Occupations	Includes 2010-38, Teacher or Administrator (elementary); 2010-39, Teacher or Administrator (secondary)
16 Entertainers and Performers, Sports and Related Workers	27-2	Includes 27-2, Entertainers and Performers, Sports and Related Workers	Includes 2010-02, Actor or Entertainer; 2010-27, Musician (performer, composer)
17 Arts, Design, and Media Workers	27-1, 27-3, 27-4	Includes 27-1, Art and Design Workers; 27-3, Media and Communication Workers; 27-4, Media and Communication Equipment Workers	Includes 2010-04, Artist; 2010-22, Interior Decorator (including designer); 2010-41, Writer or Journalist

Card Category	BLS Major or Minor Group	BLS, "99-XXXX", and "00-XXXX" Codes	"2010-XX" Codes
18 Health Diagnosing and Treating Practitioners	29-1 (excluding 29-1070, 29-1140, 29-1150, 29-1160, 29-1170)	Includes 29-1, Health Diagnosing and Treating Practitioners, except for 29-1070, Physician Assistants; 29-1140, Registered Nurses; 29-1150, Nurse Anesthetists; 29-1160, Nurse Midwives; and 29-1170, Nurse Practitioners	Includes 2010-16, Dentist (including orthodontist); 2010-31, Physician; 2010-37, Therapist (physical, occupational, speech)
19 Other Healthcare Occupations Incl. Nurses	29-2, 29-9, 29-1070, 29-1140, 29-1150, 29-1160, 29-1170	Includes 29-2, Health Technologists and Technicians; 29-9, Other Healthcare Practitioners and Technical Occupations; 29-1070, Physician Assistants; 29-1140, Registered Nurses; 29-1150, Nurse Anesthetists; 29-1160, Nurse Midwives; and 29-1170, Nurse Practitioners	Includes 2010-28, Nurse; 2010-23, Lab Technician or Hygienist
20 Protective Service Occupations	33	Includes 33, Protective Service Occupations	Includes 2010-24, Law Enforcement Officer
21 Sales and Related Occupations	41	Includes 41, Sales and Related Occupations	Includes 2010-08, Business Salesperson or Buyer
22 Office and Administrative Support Occupations	43, 23-2	Includes 43, Office and Administrative Support Occupations; and 23-2, Legal Support Workers	Includes 2010-05, Business (clerical)
23 Military Specific Occupations	55	Includes 55, Military Specific Occupations	Includes 2010-26, Military service (career)

Source: Augmented Arcidiacono Data

Note: BLS, "99-XXXX", and "00-XXXX" codes are used by applicants to the classes of 2014 – 2019, and is the only code used by applicants to the class of 2014. "2010-XXXX" codes are used by applicants to the classes of 2015 – 2019, and are used by the majority of applicants to the classes of 2015 – 2019.

9.2. Appendix B.2: Error in Prof. Arcidiacono's difference-in-difference estimates

219. In Table 6.2N of his rebuttal, Prof. Arcidiacono makes a critical error in calculating the standard error of a “double difference.” Recall that the standard error is a measure of the precision of an estimate—a smaller standard error means the estimate is more precise, (i.e., more certain) and a larger standard error means the estimate is less precise (i.e., more uncertain). This mistake leads Prof. Arcidiacono to erroneously conclude that there was a change in the difference in the academic indices and the admission rates for single and multi-racial African-American students between the classes of 2014 – 2016 and the classes of 2017 – 2019. In this section, I outline the technical nature of Prof. Arcidiacono's mistake, and describe how this mistake leads Prof. Arcidiacono to make assertions the data does not support.

220. The key error in the calculation takes place when Prof. Arcidiacono performs the following step:²¹⁸

$$s.e. (double.diff_{Error}) = \sqrt{\left[\frac{s.e. (avg.diff_{2014-2016})}{2}\right]^2 + \left[\frac{s.e. (avg.diff_{2017-2019})}{2}\right]^2}$$

221. In this formula, $s.e. (avg.diff_{2014-2016})$ is the standard error on the difference in group means from 2014 to 2016. Similarly, $s.e. (avg.diff_{2017-2019})$ is the standard error on the difference in group means from 2017 to 2019. Both of these values are correctly calculated in Prof. Arcidiacono’s report. Prof. Arcidiacono errs, however, when he divides each of the separate standard errors by two in this step. This is the approach to calculating the standard error of an average, rather than the standard error of a difference.

222. The correct approach would have been to use the formula to calculate the distribution of a linear combination of normally distribution random variables. The proper application of the formula in this instance is:

$$s.e. (double.diff_{Corrected}) = \sqrt{s.e. (avg.diff_{2014-2016})^2 + s.e. (avg.diff_{2017-2019})^2}$$

223. As shown, Prof. Arcidiacono’s mistake has the effect of making his estimates appear twice as precise as the data can actually support. After correcting this error, Prof. Arcidiacono’s conclusions can no longer be supported.

9.3. Appendix B.3: Using absolute deviation to measure the importance of unobserved characteristics is appropriate

224. In this appendix, I discuss a technical difference between how Prof. Arcidiacono and I account for the relative importance of “unobserved factors.” In section 6 of my original report, my approach for estimating this was straightforward. I used the “absolute deviation” which is the absolute value of the difference between an applicant’s predicted probability of admission according to the model and the applicant’s admissions decision. For example, if the model said a given applicant had a 25% chance of admission, and that applicant was actually admitted, unobserved factors would explain 75% of the admissions decision, and thus the absolute deviation would be 0.75. If instead that applicant were actually denied admission, then unobserved factors would explain 25% of the decision, and thus the absolute deviation would be 0.25. By comparing the average marginal

²¹⁸ Prof. Arcidiacono also makes an additional smaller mistake by failing to weight different years in the data by the correct number of observations that I have corrected. As this is less consequential than the key mistake outlined above, I do not detail the effects of that mistake here.

effect of race to the absolute deviation, we can learn about the relative importance of race, as compared to the importance of unobserved factors.

225. This is, I believe, the most clear and straightforward way to conduct this type of analysis. That is, in assessing whether race is determinative, race should be compared to all of the other factors that determine admission, both those observed and those that aren't observed, and these factors should be contextualized in terms of how much of the admissions decision they explain. Professor Arcidiacono raises a technical objection to my approach.²¹⁹ He states that the role of unobserved factors can only be properly assessed by looking at the background machinery of the logit model, rather than the probability of admission produced by the model. His objection relies on the fact that we both use a logistic model, and this model utilizes an unseen "latent" variable which allows us to estimate the probabilities and marginal effects we use in our reports. Specifically, the latent variable estimates an index of "admission strength" for each applicant that varies from negative infinity to positive infinity. This latent variable is then mapped into probabilities, which necessarily must be between 0 and 1, through the logistic function. Higher admission strength translates to a higher probability of admission but the probability of admission can never go below 0 or above 1.

226. I disagree with Prof. Arcidiacono's characterization of my approach. My approach is based on commonly accepted methods, is more transparent, and works directly with the object of interest in this setting (that is, the probability of admission). While there are many ways in which it is helpful to have an understanding of the inner workings of the logit model, the latent variable that underlies the logit model is a tool which is meant to inform us of the real world, rather than an object of interest in and of itself. Prof. Arcidiacono errs in failing to consider the practical aspects of the problem, and instead takes the machinery of the model too literally.

227. The absolute deviation I calculate in my report is referred to in the economics literature as a "generalized residual."²²⁰ These residuals are widely used in econometrics, and in fact one popular approach is based on this measure.²²¹ Professor Arcidiacono himself has relied upon this approach in his own academic work.²²² The literature describes these values as having a number of useful properties, even beyond those I describe above. They are "generalized" in the sense that the information they convey does not depend on the researcher's modeling assumption. For example, were Prof. Arcidiacono to have chosen a slightly different model (for example, the linear probability

²¹⁹ Arcidiacono Rebuttal, pp. 51–52.

²²⁰ Christian Gourieroux et al., "Generalized Residuals," *Journal of Econometrics* 34, 1987, pp. 5–32 at pp. 12–14.

²²¹ James J. Heckman, "Sample Selection Bias as a Specification Error," *Econometrica* 47(1), 1979, pp. 153–161. Technically, this paper uses a probit model, which is slightly different than the logit models Prof. Arcidiacono and I use in our reports. The principle is the same, however.

²²² Peter Arcidiacono, Jane Cooley, and Andrew Hussey, "The Economic Returns to an MBA," *International Economic Review* 49(3), 2008, pp. 873–899 at pp. 884–885.

model), he would have no choice but to concede that the absolute deviation is the right way to measure the importance of unobserved factors.

10. APPENDIX C

10.1. List of variables included in model of admission

Variable Name	Variable Description	Constructed by Arcidiacono	Card Initial Model	Card Updated Model
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 and 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	Constructed by Arcidiacono	Card initial model	Card updated model
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_abbrev	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.		✓	

Variable Name	Variable Description	Constructed by Arcidiacono	Card initial model	Card updated model
Ratings Variables (Continued)				
academic_rat_abbrev	Academic profile rating with categories: 1, 2, 3, 4, 5 and 6.	✓		✓
personal_rat_abbrev	Personal profile rating with categories: 1, 2, 3, 4, 5 and 6.	✓		✓
xtracurr_rat_abbrev	Extracurricular profile rating with categories: 1, 2, 3, 4, 5 and 6.	✓		✓
athletic_rat_abbrev	Athletic profile rating with categories: 1, 2, 3, 4, 5 and 6.	✓		✓
alum1_rat_abbrev	Alumni interview personal rating with categories: 1, 2, 3, 4, 5 or 6, and Missing.	✓		✓
alum2_rat_abbrev	Alumni interview overall rating with categories: 1, 2, 3, 4, 5 or 6, and Missing.	✓		✓
m_alum_rat	Indicator for missing alumni interviewer ratings.	✓		✓
rat2_*	Indicators for having ratings of 2 or better for each pair of profile ratings (e.g. academic and personal, athletic and extracurricular, etc.).	✓		✓
teacher1_rat_abbrev	School support rating, assigned by Admissions Committee, based on applicant's recommendation from Teacher 1. Categories: 1, 2, 3, 4, 5, and Missing.	✓		✓
teacher2_rat_abbrev	School support rating, assigned by Admissions Committee, based on applicant's recommendation from Teacher 2. Categories: 1, 2, 3, 4, 5, and Missing.	✓		✓
alum_twos	Count of alumni interview ratings (personal and overall) of 2 or better.	✓		✓
school_twos	Count of school support ratings (teacher 1, teacher 2, and guidance counselor) of 2 or better.	✓		✓

Variable Name	Variable Description	Constructed by Arcidiacono	Card initial model	Card updated model
Contextual Factors				
father_occ_cat	Mother's occupation category		✓	✓
mother_occ_cat	Father's occupation category		✓	✓
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.		✓	✓
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.		✓	✓
r_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	Constructed by Arcidiacono	Card initial model	Card updated model
High School Characteristics				
<i>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 †.</i>				
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	Constructed by Arcidiacono	Card initial model	Card updated model
Neighborhood Characteristics				
<i>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 †.</i>				
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.		✓	✓

Variable Name	Variable Description	Constructed by Arcidiacono	Card initial model	Card updated model
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.