

Online Appendices

A Modeling Admissions and the Relevant Sample

We focus on estimating the Asian American penalty among typical applicants.^{A1} This decision reflects a desire to make comparisons of similarly-situated applicants. In this section we expand on this idea, showing that consistent estimates of a penalty against typical Asian American applicants can be recovered from the subset of applications that are typical (i.e. not ALDC). Further, incorporating ALDC applicants into the estimation in a meaningful way requires stronger assumptions in order to recover consistent estimates of a penalty against typical Asian American applicants.^{A2} As we show, these assumptions are violated in the Harvard data.

In order to determine whether Harvard is discriminating against *typical* Asian Americans, it is only necessary to consider typical applicants. Consider a model of admissions where applicants compete for a fixed number of slots, N . Consider a latent index Y_i^* that represents Harvard’s perception of the quality of applicant i . All applicants above some threshold τ are admitted: if $Y_i^* > \tau$ then $Y_i = 1$ and the applicant is admitted, otherwise the applicant is rejected. That all applicants face the same admissions threshold is without loss of generality: any preferences (e.g. for ALDC applicants or particular racial groups) can be folded into Y_i^* .^{A3} The threshold τ is set to ensure the number of admits equals N .

The competition for slots manifests itself through τ . So even though, in principle, all students are competing against one another for a limited number of slots, it is still possible to estimate models of admission on subsets of the applicants, as any competitive effects will be reflected in τ .

Consider the subset of applicants that are typical (i.e. not ALDC). Further decompose

^{A1}Discrimination may occur against subgroups of applicants. For example, married women or women with children may be treated differently in the labor market than single women. Given ALDC applicants have a clear tie to Harvard, it would make sense that discrimination would be more likely among non-ALDC applicants.

^{A2}Incorporating ALDC applicants by interacting ALDC with every variable effectively allows the admissions process to operate differently for typical applicants and ALDC applicants. The addition of ALDC applicants in the fully interacted model then would have no effect on the estimates of racial discrimination against typical applicants.

^{A3}Preferences for balancing factors such as initial major interest or geography can also be included in the latent index. For example, if there are few humanities applicants in a particular admissions cycle, then humanities applicants may see higher latent indexes all else equal.

the latent index Y_i^* for these applicants into the sum of three parts:

$$Y_i^* = \alpha A_i + X_i \beta + \epsilon_i \tag{A.1}$$

(i) a part due to being Asian American, $A_i = 1$; (ii) a part due to other observables, X_i ; and (iii) a part due to unobservables, ϵ_i .

To fix ideas, consider the case where ϵ_i follows a logistic distribution and is uncorrelated with A_i and X_i . In this case, a logit model yields consistent estimates of the parameters α and β up to a scale parameter, where the scale parameter embeds the variance of ϵ .^{A4} Embedded in β will be a constant term that can be interpreted as a scaled version of τ .

Now suppose we add ALDC applicants to the data set, adding controls for their ALDC status to X_i to reflect any preferences these applicants receive. Suppose the same conditions hold as before: ϵ_i follows a logistic distribution and is uncorrelated with A_i and X_i . In this case, the additional observations increase the statistical power of the model. They do not, however, affect consistency: consistent estimates of the parameters can be obtained from a subset of the applicants.

However, if the Asian American coefficient substantially changes when ALDC applicants are added and this change is statistically significant, this suggests the model is misspecified. Either the effect of being Asian American differs for ALDC applicants, or other characteristics operate differently for ALDC applicants that in turn affect the coefficient on Asian American. Note that this is *not* a case of adding controls and having the coefficient change (i.e. omitted variable bias), but of adding observations.

One potential fix would be to allow the effect of being Asian American to vary between ALDC and typical applicants. Denoting $S_i = 1$ ($S_i = 0$) if the applicant was (was not) ALDC, we can specify the index as:

$$Y_i^* = \sum_{s=0}^1 I(S_i = s) \alpha_s A_i + X_i \beta + \epsilon_i \tag{A.2}$$

But again, if the estimate of α_0 is substantially different when ALDCs are included, this

^{A4}Note that the marginal effect of A_i is not affected by the normalization on the scale parameter.

suggests misspecification: the other variables matter in a different way for ALDC applicants, which in turn affects the Asian American coefficient.

A more general model—where ALDC status is interacted with all variables—would be:

$$Y_i^* = \sum_{s=0}^1 I(S_i = s) (\alpha_s A_i + X_i \beta_s) + \epsilon_i \quad (\text{A.3})$$

Note that this model implicitly builds in differences in the unobservables as well. By estimating separate coefficients for ALDC applicants, it allows for the possibility that the variance of ϵ is different for ALDC applicants. The coefficients for each group are all estimated relative to the underlying variances of their unobservables.

The model given in (A.3) can be estimated as two separate logits. These two logits will yield identical estimates to one where all the coefficients are estimated at once. Hence, for the purpose of estimating α_0 , estimating a logit only on typical applicants is sufficient.

As discussed in section 5.2, the effects of race on admissions *and* the effects of X_i on admissions differ for ALDC applicants. Hence our primary focus is on models that exclude ALDC applicants in order to correctly measure discrimination against typical Asian American applicants. However, the inclusion of ALDC applicants still leads to a significant penalty against typical applicants, attenuating the average marginal effect by 0.1 percentage points.

B Admissions Controls

The list below describes the full set of variables we include in each of our admissions models. Our preferred specification is Model 5. This list comes from Figure 7.1 of [Document 415-8](#), with additional information reported in Section 8.1 of [Document 415-9](#).

- Model 1: Race/ethnicity, female, disadvantaged, application waiver, applied for financial aid, first generation college student, mother's education indicators, father's education indicators, year effects, docket-by-year effects, early action, intended major
- Model 2: Model 1 plus SAT math,* SAT verbal,* SAT2 average,* missing SAT2 average times race/ethnicity, converted GPA,* academic index,* academic index squared times academic index greater than zero, academic index squared times academic index less than zero, flag for converted GPA=35 (* indicates variable was z-scored)
- Model 3: Model 2 plus female times intended major, female times race/ethnicity, race/ethnicity times disadvantaged, race times early action
- Model 4: Model 3 plus College Board variables on the characteristics of applicant high schools and home neighborhoods (many are interacted with an indicator for whether the state is an SAT majority state), whether the mother or father is deceased, whether a parent attended an Ivy League university (other than Harvard), whether a parent attended graduate school at Harvard, the type of high school the applicant attended, an indicator for rural, an indicator for being a permanent resident, and year interacted with indicators for disadvantaged, first-generation, early action, financial aid, permanent resident, intended major, flag for converted GPA=35, and missing SAT2 average
- Model 5 (Preferred): Model 4 plus indicators for each category of the academic, extracurricular, athletic, teacher 1, teacher 2, counselor, alumni personal, and alumni overall ratings, interactions with missing alumni overall rating and race/ethnicity, indicators for whether the applicant had each possible combination of a two or better on Harvard's academic, extracurricular, and athletic profile ratings, indicators for whether

the applicant had two or three 2's or better on their school support measures, and an indicator for whether the applicant had 2's or better on both of the alumni ratings

- Model 6: Model 5 plus indicators for each category of the personal rating, and indicators for whether the applicant had a two or better on Harvard's personal rating in combination with a two or better on the academic, extracurricular, and athletic profile ratings

C Discrimination in Harvard Ratings

A key advantage of working with the Harvard data to ascertain racial preferences or penalties in admissions is the availability of Harvard’s own internal ratings for each applicant. These ratings can potentially capture important applicant attributes that are unobserved to the researcher but correlated with applicant race. Including these ratings in a model of admissions will thus reduce the scope for omitted variable bias. However, if Harvard’s applicant ratings also encompass racial preferences, then they would be inappropriate controls in an admissions model aimed at estimating the role of applicant race.

In this section, we more thoroughly investigate whether Harvard’s ratings incorporate racial preferences, making them improper controls in an admissions model. To isolate the effect of race in applicant ratings, we estimate a series of ordered logit regressions where the outcome is a rating of interest, say the extracurricular rating, and the key controls include applicant race, gender, test scores, disadvantaged status, intended major, geography, neighborhood characteristics, and high school characteristics.^{A5} Importantly, in each of the ratings models, we condition on all of the other Harvard ratings, excluding the personal and overall ratings. We exclude the personal and overall ratings since, as shown in Figure 1 and additional evidence below will show, they directly incorporate racial preferences. But if there is bias against Asian Americans in some of the other ratings, controlling for these ratings will lead to an under-estimate of any bias against Asian Americans. Hence our test is quite stringent.^{A6}

Selected coefficients from the ordered logit ratings models are presented in Appendix Tables F6 and F7. For each rating, we present two models, one that is fairly sparse in terms of controls and our full model that contains a broad array of applicant attributes, including other ratings.^{A7} We present both models to illustrate how the race coefficients change as controls are added—information which can be used as a guide to how unobservables correlate with race. Broadly speaking, the racial categories for African American, Hispanic, and

^{A5}There are no estimates of the athletic rating in the public record but we do control for it in our preferred ratings models.

^{A6}For a full description of the variables included in the ratings models, see [Document 415-8](#) and [Document 415-9](#).

^{A7}Models with subsets of the controls can be found in [Document 415-9](#) Tables B.6.1R–B.6.2R.

Asian American are statistically significant across most of the ratings models. However, the magnitudes, signs, and patterns in the coefficients as controls are added are quite different across Harvard's ratings.

In our full model, the Asian American coefficient is positive and significant for three of the ratings: the academic, extracurricular, and the alumni overall rating. But in each of these cases the Asian American coefficient—and indeed all the race coefficients—is much smaller in the specification of the full model than in the sparse model.^{A8} A very different pattern emerges for the personal and overall rating. In our preferred models of the personal and overall rating, the Asian American coefficient is large and negative while the African American coefficient is large and positive, with the gaps growing between the sparse and full models. To put the magnitude of these coefficients in context, we calculate the change in the probability of obtaining a 2 or better for an Asian American if we were to switch their race, all else equal. If Asian American applicants were treated as African American (white) applicants, their probability of obtaining a 2 or better on the personal rating would increase by 59% (21%).^{A9}

The large race coefficients in the estimated models for the personal and overall ratings suggest that racial preferences are an important factor in the assignment of these ratings. Further evidence that these coefficients arise from racial preferences can be seen in how the coefficients change between our sparse and full models. Appendix Figure F1 illustrates how the estimated racial gap between Asian American and African American applicants changes as controls are added for the academic, extracurricular, personal, and overall ratings. For the academic and extracurricular models, when we add controls the racial gap between these two groups shrinks towards zero. Note that, in our preferred ratings model, we interact race with gender and disadvantaged status. As a result, we show the male/female range for the estimated gap by disadvantaged status.

A very different pattern emerges for the personal and overall ratings. For the personal rating, the estimated racial gap between Asian American and African American applicants expands significantly as more controls are added. This is especially true for non-disadvantaged

^{A8}Although here we are referring to the base coefficient, the finding of a diminished effect of race holds for any set of interactions as well.

^{A9}See Table 6.1R in [Document 415-9](#) for further details.

applicants who account for the vast majority of applicants. The expansion of the estimated gap suggests that the race coefficients are picking up racial preferences. A similar pattern is observed for the overall rating, where not only does the racial gap between Asian American and African American applicants expand as controls are added, it actually reverses sign. In the sparse model, Asian Americans receive higher overall ratings relative to African Americans, but when all the controls are added, Asian American applicants appear significantly worse.

Examining how the race coefficients change as we alter the set of controls speaks to the relative strength of each group on the observable components in the model. This is useful information, since economists often assume that selection on unobservables works in the same direction as selection on observables. We take this idea one step further by evaluating the average “observed” strength for each racial group across the various Harvard ratings. In particular, we calculate the index of observables (except race and year) for each applicant by multiplying their observable characteristics with the estimated coefficients and summing all the terms. We then subtract off the white mean of the observables index and divide by the variance. Finally, we average within each racial group, labeling this quantity the average index. The average index measures how strong each group is on observable characteristics associated with each rating relative to whites, while the race coefficients measure racial preferences and differences in unobservable characteristics common within racial groups. When the race coefficient and average index move in opposite directions, the case for race playing a role in the rating—as opposed to just proxying for unobserved characteristics—is strengthened. This pattern can only occur if either racial preferences are strong and/or selection on observables works in the opposite direction as selection on unobservables.

The race coefficients and average indices for all of Harvard’s ratings are displayed in Appendix Table F8.^{A10} In Appendix Figure F3 we graphically display the race coefficients and average index for the academic, extracurricular, overall, and personal ratings. For the academic and extracurricular ratings, the race coefficients have the same signs as the index of observables. This suggests that if we were able to add even more controls, the race effects would likely attenuate to zero. For example, in the case of academics, we exclude information

^{A10}The full sets of ratings model coefficients are available in Tables B.6.1R–B.6.4R of [Document 415-9](#).

related to the number of AP exams, AP exam scores, and academic awards.^{A11} We know from Table 1 that Asian Americans are stronger on AP exams, and are likely stronger on other unobserved academic measures.^{A12}

While the race coefficients in the academic and extracurricular ratings likely reflect selection on unobservables, this is not the case for the overall rating. The race-related coefficients move in the opposite direction of the average index. African American and Hispanic applicants are worse on the average index, while Asian American applicants are stronger. In fact, the ordering of all the race coefficients and average index values is exactly opposite: the order of the race coefficients from largest to smallest is African American, Hispanic, White, and Asian American while the reverse pattern is seen in the average index. A conflicting pattern between the race coefficients and the observable strength of each group is strong evidence of racial preferences. Supporting this interpretation is the fact that Harvard acknowledges that the overall rating incorporates racial preferences.^{A13}

The personal rating shows the same pattern as the overall rating. African American and Hispanic applicants receive large bumps in their personal ratings when controlling for all other factors (including all the other ratings other than the overall rating), but are worse on the average index. Asian American applicants, on the other hand, are penalized relative to white applicants but are stronger on the observables that predict the personal rating. Again, the ordering of the race coefficients and average indices by racial group is flipped. This pattern strongly suggests that racial preferences play a large role in the personal rating, similar to the overall rating. As a result, it is incorrect to include the personal and overall ratings in an admissions model focused on estimating racial preferences unless the researcher also calculated the effect of racial preferences through these ratings.

While not displayed in Appendix Figure F3, there is also evidence that Asian American applicants are discriminated against in the school support ratings and alumni personal rating.

^{A11}AP exam data is only available for the last two admissions cycles contained in the data.

^{A12}The positive coefficient for Asian American applicants in the extracurricular rating model likely reflects differences in the underlying activities that Asian Americans pursue, relative to whites, which are not captured by the model. For example, 45% (27%) of the primary extracurricular activities for white (Asian American) applicants are sports-related, leaving more lines available on the college application for Asian Americans to report non-sports related activities. Note that these numbers include ALDC applicants, see Trial Exhibit DX 680.

^{A13}See Document 421-9, pp. 259, 288 and 422.

For each of these ratings, the Asian American coefficient is negative and significant, while Asian American applicants are stronger than white applicants on the index of observables. Since the size of the racial penalty in each of these ratings is substantially smaller than for the personal rating, we take a conservative approach and include these ratings in our preferred admissions model. However, it is important to point out that, by controlling for the school support and alumni personal ratings in all the other ratings models, we are stacking the deck against finding evidence of discrimination. The fact that we still find strong evidence of racial preferences in the overall and personal rating is all the more compelling.

Going beyond selection on observables versus selection on unobservables, there is additional evidence that the personal rating is a tool to implement Harvard's preferences over the composition of their admits. For example, in the personal rating model the interaction between African American and female and African American and disadvantaged are significantly negative, implying racial preferences are muted for these two groups. The share of applicants who are female or disadvantaged is significantly higher for African Americans than for any of the other three major racial/ethnic groups, so if Harvard is interested in balancing within-race characteristics then we would expect to see muted preferences for African American applicants who were female or disadvantaged.^{A14} The only other rating that has this pattern is the overall rating, a rating that we know Harvard uses to directly implement preferences.^{A15}

^{A14}Table 3.1R of [Document 415-9](#) shows descriptive statistics by racial/ethnic group, including share female and share disadvantaged.

^{A15}Harvard appears to use the overall and personal ratings to give bonuses for other groups as well. As discussed in [Arcidiacono, Kinsler, and Ransom \(2022, footnote 27\)](#), ordered logit models of the ratings that further include LDC applicants show either no legacy tip or a very small tip except in two cases: legacies receive a significant bonus in both the overall and personal ratings.

D Model Fit

In this section, we describe how information in the public domain helps us more precisely estimate the underlying distribution of the index of applicant observables, AI_i . To pin down the shape of the observable index distribution, we rely on the observed admit rates across deciles of the true AI_i distribution for Asian Americans. These admit rates are presented in Table 9.1 of [Document 415-9](#).

We build off the simple approach described in the text by drawing an initial index for each applicant from a standard normal distribution. Given the initial draw, applicants are sorted into deciles. We then add flexibility by assuming the true underlying distribution of observables is a weighted sum of the initial draw, its square, its square interacted with whether the value was positive, and its exponential. The predicted admit rates for decile k are then calculated as the average of $\frac{\exp(AI_{ik})}{1+\exp(AI_{ik})}$ for all i applicants in decile k . The weights on the various components of the distribution are estimated using the method of simulated moments, matching the predicted admit rates by decile to the observed distribution of admit rates across deciles for Asian American applicants.

Table F9 illustrates that the estimated flexible distribution precisely matches the observed Asian American admit rates across the deciles of the admissions index. For comparison purposes we also show how well a standard normal and log-normal distribution match the data. While the normal distribution does fairly well, the log-normal struggles to match admit rates in the left tail of the distribution.

To calculate the implied R^2 assuming that AI_i is distributed according to the estimated flexible distribution, we complete the following steps.

1. With the underlying distribution of AI_i known, take draws from this distribution (using its parameter estimates obtained from the method of simulated moments estimation described above) and draw ϵ_i 's from a logistic distribution.^{A16} Assign the highest N_A values of $AI_i + \epsilon_i$ to match the total number of admits to Harvard.
2. Calibrate a logit model of the simulated admissions decisions from the previous step

^{A16}Implicit in this step is an assumption that the distribution of AI_i for the population has a similar shape to the distribution of AI_i for Asian Americans.

on AI_i and a constant such that the overall admit rate and the Pseudo R^2 match the actual Harvard data and the admissions model from [Document 415-9](#).

The coefficient on AI_i will be larger (smaller) than one if the variance for Asian Americans is smaller (larger) than the variance for the populations as a whole.

3. Compute the implied R^2 of the model, which is the fraction of variance in $AI_i + \epsilon_i$ explained by AI_i :

$$\begin{aligned} R^2 &= \frac{\text{Var}(AI_i)}{\text{Var}(AI_i + \epsilon_i)} \\ &= \frac{\text{Var}(AI_i)}{\text{Var}(AI_i) + \frac{\pi^2}{3}} \end{aligned}$$

The implied R^2 under the flexible distribution for AI_i is 0.89. It is important to note that this value is a bit misleading. The increase in the R^2 of our flexible distribution relative to the normal distribution comes from the left tail of the distribution: those who have virtually no chance of being admitted.

While the R^2 of the latent index is sensitive to the tails of the distribution, this is not true of accuracy. Assuming AI_i is normally distributed results in an accuracy rate for admits of 64.07%; using the flexible distribution results in an accuracy of 64.09%.^{A17} The overall accuracy rate is 96.08% and 96.09%, respectively. Note that an admissions model with no controls would lead to an overall accuracy rate of 90%.^{A18}

^{A17}The accuracy rate for admits is calculated as the share of the 5.45% of simulated admits based on AI_i and ϵ_i that are in the top 5.45% of the AI_i distribution.

^{A18}An admissions model with no controls would randomly assign 5.45% of applicants as admits and 94.55% as rejects. The accuracy rate would then be given by $94.55\% \times 94.55\% + 5.45\% \times 5.45\% = 90.05\%$.

E Difference in the Expert Reports

The results in this paper form the basis of the plaintiff’s argument in the *SFFA v. Harvard* lawsuit with regard to Asian American discrimination. Peter Arcidiacono served as expert witness for the plaintiff in the lawsuit, while David Card was the defendant’s expert witness. Once the reports of the two experts became public, a set of economists led by Michael Keane filed a brief in support of Arcidiacono’s analysis on three key dimensions: (i) the exclusion of ALDC applicants from the model, (ii) the exclusion of the personal rating from the model, and (iii) the interaction of race with disadvantage status.^{A19} As we illustrate below—taking everything else Card did at face value—either removing the personal rating or both excluding ALDCs and interacting race with disadvantaged status results in a negative and significant penalty against Asian Americans.

In response to the Keane brief and in support of Card, a number of other prominent economists (led by Sue Dynarski) signed an amicus brief rebutting these points.^{A20} The stature of these individuals in the field—which includes two Nobel Prize winners and two of the top economists in President Biden’s administration—as well as the stature of Card has lent great weight to their claims, despite the flaws and internal inconsistencies in their arguments.^{A21}

The purpose of this appendix is twofold. First, we directly address the differences between our model and Card’s model, focusing on the key issues in the Keane and Dynarski briefs. Here we make clear that modeling assumptions employed by Card and supported by the Dynarski brief conflict with standard practices followed by the rest of the field of economics. Second, we illustrate that the only way to generate a finding of no Asian American

^{A19}See <https://docs.justia.com/cases/federal/district-courts/massachusetts/madce/1:2014cv14176/165519/450>. Followup briefs can be found here <https://docs.justia.com/cases/federal/district-courts/massachusetts/madce/1:2014cv14176/165519/624> and here <https://raw.githubusercontent.com/tyleransom/SFFAvHarvard-Docs/master/AmicusBriefs/SFFAappellateAmicusBrief.pdf> with additional signatories.

^{A20}<https://docs.justia.com/cases/federal/district-courts/massachusetts/madce/1:2014cv14176/165519/499>. A follow-up brief is available at https://admissionscase.harvard.edu/files/adm-case/files/legal_-_filing_-_200521_-_economists_-_2020.05.21-15_-_brief_for_amicus_curiae_professors_of_economics.pdf.

^{A21}The *SFFA v. Harvard* lawsuit was also focused on the size of racial preferences in admissions. The desire to preserve those preferences may have served as the rationale for the Dynarski briefs supporting such a flawed approach. However, the Dynarski briefs were focused solely on the Asian-American discrimination claim, not whether Harvard’s racial preferences were appropriate.

discrimination using the Harvard data is to make multiple modeling choices that are each at odds with standard approaches.

E.1 Modeling Differences

The key finding from our analysis is that typical Asian American applicants to Harvard are held to a higher standard than their white counterparts. If the average Asian American applicant were treated like a white applicant, their admit rate would increase by 1 percentage point off a baseline admit rate of approximately 5%. Yet, Card is able to generate a finding of no Asian American discrimination. We first outline the three key differences between our model and Card's. We then discuss other differences where there is more room for debate or where the differences are sufficiently small as to not warrant attention. Our findings are robust to all of these other differences in modeling choices.

We now discuss the three key issues that serve as the points of contention in the Keane and Dynarski briefs and explain why the approach by Card is incorrect.

1. **Inclusion of ALDCs:** Card and the Dynarski brief argue that it is not possible to estimate admission preferences for typical applicants without also including in the model recruited athlete, legacy, dean's list, and faculty/staff related applicants (ALDC). From an econometric perspective this is incorrect. Admissions preferences for typical (non-ALDC) applicants can be recovered by estimating a model including only typical applicants, despite the fact that the two groups are competing for the same seats. The strength of the ALDC pool will be reflected in the admission threshold typical applicants need to overcome to be admitted. A more detailed argument is provided in Appendix A. The inconsistency of this argument can be seen in the treatment of foreign applicants by both experts.^{A22} Neither expert used foreign applicants in the estimation of their models despite foreign applicants being a part of the admissions process and making up more than 10% of the admitted class each year. Yet, Card did not claim that the admissions models are biased by the exclusion of this applicant group.

^{A22}The inconsistency is also revealed by Card's analysis focusing only on female applicants and only on applicants from California. Given that the model that Card uses for his subgroup analysis makes the same faulty assumptions as the one that produced a null effect for Asian Americans as a whole, it is also no surprise that it produced a null effect for these subgroups.

The reason why it is important to exclude ALDC applicants is that preferences work differently for this group. For example, Table 6 in [Arcidiacono, Kinsler, and Ransom \(2022\)](#) shows that academic and extracurricular ratings matter less for ALDC applicants, and thus including them in the model without fully interacting everything distorts these estimates for typical applicants. Rather than interact ALDC with all other attributes, we take the simpler approach and exclude them from the model. Note that more than 97% of Asian American applicants are typical applicants.

Not only does Card include ALDC applicants in his admissions model, he includes them in all of his descriptive analysis. This is misleading since he makes claims about the relative strengths of white and Asian American applicants that are distorted by the presence of ALDC applicants. As an example, in Exhibit 2 of Card's rebuttal report ([Document 419-143](#)), he compares how Asian American and white applicants fare on Harvard's academic, extracurricular, personal, and athletic ratings individually as well as the likelihood of obtaining a two or better on at least three ratings. Since recruited athletes receive high athletic ratings and ALDC applicants as a group tend to receive high personal ratings, these comparisons are uninformative about how typical Asian American applicants compare to typical white applicants. This pattern of ALDC inclusion is repeated throughout Card's reports; indeed, Card does not do any analysis where ALDC applicants are taken out.^{A23} As a result, much of the supporting evidence Card relies on to argue that Asian American applicants are weaker on non-academic dimensions or *less multidimensional than white applicants* is not germane to our sample of typical applicants.

While we believe our decision to exclude ALDC applicants is appropriate, estimates of the Asian American penalty for typical applicants remain large and statistically significant when ALDC applicants are included in the model. Table 7.2R of [Document 415-9](#) shows that the probability of admission for a typical Asian American applicant increases from 5.2% to 6.1% when treated as a white applicant even when legacy,

^{A23}This is in contrast to Arcidiacono, who does his analysis both with and without ALDC applicants. Moreover, Harvard's own Office of Institutional Research (OIR) presents descriptive analysis that excludes legacies and athletes (see [Trial Exhibit P009](#) and Appendix Figure F2).

donor, and faculty/staff applicants (LDC) are included in the model.^{A24} Without LDC applicants in the model, the same thought experiment yields an increase in admissions chances from 5.2% to 6.2%. While we have not estimated our preferred admissions model with recruited athletes, Tables B.7.1 and B.7.2 of [Document 415-8](#) illustrate that in a slightly altered admissions model, the addition of ALDC applicants mildly reduces the negative impact of Asian American status for typical applicants.^{A25} This is similar to what we find when adding only LDC applicants to our preferred specification. There are two important takeaways from the admissions models that include ALDC applicants. First, the estimated penalty for typical Asian American applicants remains large and statistically significant. Second, there is no evidence of an Asian American penalty for ALDC applicants. These two results are not in conflict, as there is no ex-ante reason why discrimination should work the same across all groups of applicants. In fact, by belonging to one of the special applicant groups, Asian American applicants may be able to overcome stereotypes that hold typical Asian American applicants back. The lack of a penalty against Asian American ALDC applicants should not diminish claims that Harvard employs admissions practices that discriminate against Asian Americans. More than 97% of Asian American applicants are not ALDC, meaning that nearly all Asian American applicants face an explicit penalty in admissions. Moreover, the very existence of ALDC preferences works to the detriment of the overwhelming majority of Asian Americans. ALDC applicants are predominantly white, and as we show in [Arcidiacono, Kinsler, and Ransom \(2022\)](#), the elimination of either legacy or athlete preferences would increase the number of Asian American admits by more than 4%.

- 2. Inclusion of Personal Rating:** Card and the Dynarski brief argue that Harvard's personal rating is an appropriate control in an admissions model whose purpose is to estimate racial preferences. By Card's own admission, if a control directly incorporates

^{A24}When LDC applicants are included, the model also includes indicator variables for legacy, double legacy, faculty or staff child, donor connections, interactions between legacy and race, and interactions between faculty/staff/donor connections and race.

^{A25}See Section 8 of [Document 415-9](#) for a detailed discussion of how this model differs from our preferred model.

racial preferences, it is improper (see page 10 of [Document 419-141](#)). Below we discuss the overwhelming evidence that racial preferences influence the personal rating.

Descriptive Support

There is a strong positive relationship between academic strength and the personal rating—and indeed all the ratings. See Tables [F2](#), [F3](#), and [F4](#). Yet, despite being strongest on academics, Asian Americans score the worst on the personal rating. To put this in perspective, African Americans in the top decile (10th) of academic strength receive high personal ratings at over twice the rate of African Americans in the 3rd decile; both score better than Asian Americans in the top decile.

The overall rating is explicitly allowed to incorporate racial preferences, and in fact Card excludes the overall rating from his models on these grounds. Yet, the descriptive patterns for race and academic index decile are fundamentally the same for the personal rating and overall rating (see [Figure 1](#) and [Table 4](#)). All other ratings show reasonably consistent patterns with regard to race within academic index deciles except these two. One could argue that the personal rating is different in that it could reflect overcoming socioeconomic disadvantage or racism. But Asian Americans are substantially more likely than whites to be classified as disadvantaged ([Table 1](#)) and surely would be more likely to experience discrimination than their white counterparts.

Support from Ratings Models

Estimates of models of the personal rating show a large penalty against Asian Americans regardless of the set of controls (see [Table F7](#); for all the intermediate models see [Table B.6.3R](#) of [Document 415-9](#)). The coefficient on Asian American in the personal rating model is twice the magnitude of any of the other ratings models (see [Tables F6](#) and [F7](#)). More importantly, the overall effect on the personal rating is substantial: if Asian Americans were treated as whites their average probability of getting a 2 or better on the personal rating would increase from 17.8% to 21.6%, an over 20% increase.

One concern is that the personal rating model suffers from omitted variable bias. How-

ever, Asian Americans are on average stronger than all racial groups on the observables associated with the personal rating and all other ratings (see Figure F3 and Table F8). Further, Asian Americans are at least as strong as whites on the non-academic observables associated with the personal rating (see Table B.6.13R of Document 415-9). Following Altonji, Elder, and Taber (2005), we would expect any selection on unobservables to move in the same direction as observables, implying that we are likely *underestimating* the penalty Asian Americans receive in the personal rating.

Finally, the personal and overall ratings are the only ones where: (1) the ordering of the race coefficients is the opposite of the strength of the racial groups on the observables (2) the Female x African American coefficient is negative and significant, and (3) the Disadvantaged x African American coefficient is negative and significant (see Tables F6, F7, and F8). These last two patterns are consistent with using the personal and overall ratings to balance within-race gender and disadvantaged status. The fact that these two ratings behave so similarly again suggests that the personal rating incorporates racial preferences since Harvard acknowledges that the overall rating can be a function of race.

Support from Alumni Ratings

While Harvard admissions staff do not typically interview applicants, Harvard alumni do. And here we find a much smaller penalty on the personal rating assigned by alumni who actually meet the applicant, consistent with actually meeting the applicant reducing stereotypes (see Table F7). Additionally, alumni interviews are the place where one might expect discrimination to occur, since alumni have not experienced the same type of training as admissions staff, particularly as it relates to implicit bias. Yet, alumni rate Asian American applicants higher.

Support from UNC

The University of North Carolina (UNC) also uses a personal rating to evaluate applicants. While UNC is not quite as competitive as Harvard, out-of-state admit rates

at UNC are around 13%, making it a highly competitive university. In contrast to Harvard, Asian American applicants to UNC are rated just as well as whites on the personal rating and there is no evidence of Asian American discrimination in admissions. This further illustrates that Harvard is using the personal rating as a means of racial balancing (see footnote 53).

In addition to all of the above, Harvard’s own behavior regarding the personal rating suggests that race was a factor admissions staff took into account when assigning a score. During the period we study, Harvard’s guidelines for assigning the personal rating made no indication that race could not be used (Trial Exhibit P001). However, in the summer prior to the start of the *SFFA v. Harvard* trial, Harvard altered its guidelines for assigning the personal rating to explicitly state that race was not to be considered (Trial Exhibit P633).

It is important to point out that Card estimates no models of the personal rating that do not show a significant and large negative penalty against Asian Americans.^{A26} He also shows no evidence that Asian Americans are worse than white applicants on the observables—as a whole or non-academic—associated with the personal rating. Rather, Card argues that Asian Americans are worse on non-academic factors in his model of *admissions* where preferences for ALDC applicants are *included* as part of the non-academic factors.^{A27} Note that excluding the personal rating, but taking Card’s approach on every other modeling choice—including having ALDCs in the estimation sample—reveals a negative and significant penalty against Asian Americans.

It is difficult to argue that Asian Americans are not discriminated against in the per-

^{A26}Card does present an analysis where he ‘corrects’ the personal rating by using the predicted values absent race from Arcidiacono’s rating model. This correction is also applied to the academic and extracurricular ratings but to none of the other ratings. Since all the variables that appear in the models of the ratings also appear in the admissions model, there is no exclusion restriction and the model will approximate one where these three ratings are excluded, with the difference being the non-linearities in the controls. Doing this—along with Card’s other assumptions including keeping ALDCs in the sample—does not show a significant penalty. However, removing *all* the ratings does show a penalty against Asian Americans. See column (4) of Tables B.7.1R and B.7.2R in Document 415-9.

^{A27}See Document 419-143 (p. 30) and the trial judge’s ruling (Document 672, p. 58) where these results were cited.

sonal rating given the consistently large, negative, and significant effect of being Asian American in all models of the personal rating. Asian Americans are also stronger on the observables associated with the personal rating, suggesting that they are likely stronger on the unobserved components as well. Arguing that the personal rating is an appropriate control in an admissions model whose purpose is to estimate racial preferences sets a dangerous precedent. An institution can simply create a rating—say, likability—and then implement discrimination through the rating. Any accusation of discrimination can then be rebuffed by simply claiming members of the discriminated group are not likable.

As we discuss in Section 5.1, adding the personal rating to our preferred admissions model cuts the Asian American penalty by less than half. Even if one believes the personal rating to be an appropriate control (despite the overwhelming evidence to the contrary), there is still evidence of a large and statistically significant penalty for typical Asian Americans. We believe a more reasonable interpretation is that bias in the personal rating accounts for a little less than half of the Asian American admissions penalty.

3. **Exclusion of Race-Disadvantaged Interactions:** Card and the Dynarski brief argue that it is improper to include interactions between race and disadvantaged status in the admissions model, believing there is no theoretical basis for doing so.^{A28} However, including these interactions in the model reveals that disadvantaged status matters quite differently for African American and Hispanic applicants. This is especially true for African Americans who receive no bump for being disadvantaged. Card himself writes, “The typical approach ... would be to include an interaction between race and disadvantaged status only if the effect of being disadvantaged is different for Asian-American and White applicants (or, equivalently, if the effect of race is different for disadvantaged and non-disadvantaged applicants)” (see page 49 of [Document 419-141](#)).

Including interactions between disadvantaged status and race matters for estimating

^{A28}That there is no theoretical basis for doing so is false. Indeed, Harvard’s own Office of Institutional Research (OIR) estimated admissions models that included these interactions ([Trial Exhibit P009](#) and [Trial Exhibit P028](#)). See [Arcidiacono \(2005\)](#) for a similar approach.

the magnitude of Asian American discrimination. Because African American and Hispanic applicants receive smaller bumps for being disadvantaged, excluding the interactions dilutes the overall impact of disadvantaged status on admissions. This results in a smaller estimated Asian American penalty since Asian American applicants are significantly more likely to be disadvantaged relative to white applicants.

On these three important modeling differences, the positions taken by Card (and supported by the Dynarski briefs) are simply not defensible for evaluating how and whether discrimination occurs against Asian American applicants. The fact that these modeling choices are needed to defend Harvard provides strong supporting evidence of the strength of the Asian American discrimination finding.

There are other differences between the Arcidiacono and Card models. Some are minor and others are not as clear as the three issues above. We go through each of these points here, explain why we made the modeling choices we did, and note that none of them affect the finding of an Asian American penalty in Harvard admissions.

1. **Inclusion of Staff Interview:** Card argues for the inclusion of an indicator for receiving a staff interview in the admissions model. This indicator is basically irrelevant when ALDC applicants are excluded, as only 1.3% of typical applicants receive an interview. However, over 20% of ALDC applicants receive an interview. Thus, access to obtaining a staff interview is clearly a function of applicant status, and will likely relate to other attributes, including race. This is also consistent with how Card treats the variable, choosing to include an indicator for obtaining an interview instead of the resulting applicant rating generated by the staff member. It is also relevant to Card's claims that whites are stronger than Asian Americans on nonacademic characteristics as this is one of the controls included.^{A29}
2. **Inclusion of parental occupation and intended career:** Card argues for the inclusion of parental occupation and intended career in the admissions model. In principle this is a reasonable point. We do not include these variables in our preferred model

^{A29}While such a low rate among typical applicants would make little difference to the *average* characteristics of applicants, it is relevant for the share in the top 10% of applicants which is where the claim is made.

because how they are coded is wildly inconsistent across admissions cycles, forcing the analyst to make a number of *ad hoc* choices regarding how to code and combine various groupings to generate a consistent measure. This, coupled with the fact that there are numerous other variables already included in the model that capture parental background and the interests of the applicants, is why we exclude these variables in our preferred model.

To illustrate, in the database made available as part of *SFFA v. Harvard*, parental occupation is available through the Common Application using either a Bureau of Labor Statistics (BLS) code or a Common Application code. The use of the two codes varies across cycles and the categories within each occupation code change over time. Appendix Table F10 provides evidence on the inconsistency of the parental occupation variables. For example, between the Classes of 2014 and 2015, the number of fathers in the ‘Other’ occupation classification nearly triples from 1,593 to 4,608. Between 2017 and 2018, the number of fathers who are unemployed drops from 1,300 to 5.

In addition to the lack of consistency, there is little evidence that parental occupation matters beyond helping to determine whether an applicant is disadvantaged. While parental occupation is included on an applicant’s summary sheet, it does not appear to be an important part of the evaluation process. For example, the reader guidelines for 2017 (Trial Exhibit DX 016), 2018 (Trial Exhibit P001), 2019 (Trial Exhibit P071), and 2023 (Trial Exhibit P633) never discuss parental occupation, but do discuss scores, ratings, interviews, GPA, disadvantaged status, etc.^{A30} Additional evidence on the inconsequential impact of parental occupation comes from Trial Exhibit DX 024, a discussion guide for the 2012 casebook. This guide walks readers through 12 pseudo applications and discusses key features of each application and admissions outcomes. Across the 12 applicants and 12 pages of discussion, parental occupation is never discussed beyond one mention of a parent being blue-collar.^{A31} For these reasons,

^{A30}Further evidence that parental occupation is unimportant comes from Trial Exhibit P238. This document shows an internal email conversation among Harvard employees early in the admissions cycle for the Class of 2017. The following is a direct quote from the email, “RMW just noticed that parent2 employer field not showing up on the reader sheets. Turns out I had cut it by accident...Though if they’re only just noticing this now, I do wonder how important it is or how carefully they’re paying attention.”

^{A31}Parental occupation is discussed in deposition testimony as a tool to infer disadvantaged status. See p.

we exclude parental occupation from our preferred model. For similar reasons, we exclude an applicant’s intended career. This is a variable that varies considerably across admissions cycles and—since we already account for intended major—seems unnecessary.^{A32}

Card advocates including both of these variables ([Document 419-141](#)). For the occupation controls, Card harmonizes the reported parental occupation codes by mapping Common Application codes to major and minor groups in the BLS-Standard Occupational Classification System. Major and minor groups are then combined into broad occupational categories. There are 24 occupational classifications for mothers and fathers, with little explanation for the chosen groupings. For example, business executive, business and financial operations, and other management are included as separate categories. Low skill is separate from construction and protective service. Further evidence that the occupation variables are not especially informative is that the second most common occupation among both mothers and fathers is “Other” (see pp. 178–179 of [Document 419-141](#)).

While we believe the occupation category and intended career variables are unreliable and superfluous, we test the robustness of our preferred model to their inclusion.^{A33} When occupation and intended career are added to the preferred model, the average marginal effect associated with being Asian American is -0.75% and statistically significant at the 5% level.^{A34} While smaller than our preferred model estimates, it still indicates a large penalty for Asian American applicants relative to white applicants.

3. Pooled vs Yearly Model: Card and those who signed the Dynarski amicus brief argue that the appropriate approach for estimating Harvard admission preferences is

201 of [Document 421-9](#) (“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.”); p. 59 of the deposition of Christopher Looby (“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.”) [[Document 419-143](#), fn. 56].

^{A32}See Appendix Table F11 for information on how intended career varies by admissions cycle. Intended career is also never discussed in the reader guidelines made public over the course of the trial: 2017 ([Trial Exhibit DX 016](#)), 2018 ([Trial Exhibit P001](#)), 2019 ([Trial Exhibit P071](#)) or 2023 ([Trial Exhibit P633](#)).

^{A33}Adding these 64 variables to the model increases the total number of controls by more than 15%.

^{A34}See Table 8.2N in [Document 415-9](#).

to estimate separate models for each admission cycle (six in all). We disagree and argue that a pooled model with appropriate interactions between admission cycle and applicant characteristics is superior. In particular, we include interactions between admission cycle and applicant characteristics such as gender, disadvantaged status, and intended major. These interactions allow Harvard to balance their class along these dimensions each cycle. However, there is no reason to believe that Harvard values test scores, high school GPA, and profile ratings differently each year. As the next section will show, this disagreement has very little impact on the results. If we estimate Card’s yearly models under a more reasonable set of assumptions as outlined above, a large and statistically significant Asian American penalty emerges.

There are other minor differences between Card’s model and ours, but they have little impact on the findings and have received little attention from the signatories of either side’s amicus brief. In the next section, we turn to Card’s model and show the fragility of his no discrimination finding.

Before jumping to Card’s model, it is also important to point out that Harvard’s Office of Institutional Research (OIR) reports admissions model estimates in [Trial Exhibit P009](#) and [Trial Exhibit P028](#) that pool application cycles, include both ALDC applicants and the personal rating, but also include race-by-disadvantaged status interactions. In each of these models, there is a statistically significant Asian American penalty.^{A35}

E.2 The Fragility of a No Discrimination Finding

In this section we start from Card’s baseline specification where he finds an insignificant Asian American penalty, and explore how simple and reasonable alterations from this baseline lead to changes. The broader point is that, while our preferred specification is quite robust, Card’s specification that finds no penalty is very fragile. In all of the analysis below we focus on modeling admissions for typical applicants since this is the appropriate sample to study.

^{A35}The OIR models respectively cover the Classes of 2007–2016 ([Trial Exhibit P009](#)) and 2009–2016 ([Trial Exhibit P028](#)). Both sets of models also include foreign applicants, which are completely excluded from the expert reports on both sides of the *SFFA v. Harvard* case.

E.2.1 Pooled Models

We begin by exploring the sensitivity of a pooled admissions model proposed by Card that is capable of generating a small and insignificant Asian American penalty. This is not Card’s preferred model, but is a good starting point for understanding the importance of the assumptions related to the controls included in the model. For full details of the model, see Section 5 of [Document 419-141](#). Again, we focus on versions of this model that exclude ALDC applicants, but it is important to note that Card never estimates an admissions model excluding this special set. As we illustrated earlier in [Appendix A](#), it is inappropriate to include these applicants unless indicators for ALDC are interacted with all the other applicant attributes. A simpler approach is to just exclude them.

The key differences between Card’s pooled model and our preferred pooled specification are: (i) inclusion of the personal rating; (ii) exclusion of interactions between race and disadvantaged status; and (iii) inclusion of parental occupation.^{A36} [Appendix Table F12](#) shows how Card’s estimated Asian American penalty is affected by the modeling choices associated with points (i)–(iii). The first row shows that it is possible to construct a pooled admissions model that yields no statistically significant Asian American penalty. The remaining rows show that changing any of the three questionable modeling choices results in a statistically significant Asian American penalty.^{A37} Moreover, altering all three components essentially leads to a result that is almost identical to our preferred specification. Thus, the other differences between our preferred model and Card’s pooled model have a relatively minor impact.

^{A36}While these three differences will be our primary focus, there are other differences between the models. See [Document 415-9](#) for a discussion.

^{A37}As discussed in the previous section, the inclusion of race by disadvantaged status is necessitated by the differential effect disadvantaged status has for African American and Hispanic applicants. To see this, rather than interact race with disadvantaged status, we estimate two alternative models where we: 1) include only white and Asian American applicants, and 2) include only non-disadvantaged applicants. In both cases the estimated Asian American penalty is statistically significant and slightly larger than when we interact race and disadvantaged status using the full sample (see rows 3 and 4 of [Table F12](#)).

E.2.2 Yearly Models

While Card estimates a pooled admissions model (Document 419-141), his preferred approach is one that estimates admissions preferences separately by year.^{A38} The structure of the yearly models is essentially identical to the pooled model in terms of included controls. The benefit of the yearly approach is it allows for variability in the impact of applicant attributes over time. The cost is reduced statistical power and the potential for model overfitting. Approximately 2,000 applicants are admitted each year, and the yearly models will contain well over 200 variables each. In contrast, the pooled model includes approximately 350 variables, but there are more than 11,000 admits across all cycles.

One important difference between Card’s pooled and yearly models is the inclusion of total work hours and indicators for an applicant’s primary extracurricular activities. The reason these variables are excluded from the pooled model is that they are only available for applicants to the Classes of 2017–2019.^{A39} However, the decision to use the detailed extracurricular activities in this particular manner is odd. Data on extracurricular activities come from applicants listing each activity they participated in, the years in which they participated in this activity, the hours per week and weeks per year they participated in the activity, and whether their participation was during the school year or outside the school year. Each of the activities is assigned to one of 29 categories (e.g., work, academics, musical instruments). Card defines a primary activity as an activity the applicant lists in the first or second activity field of her application (Document 419-141). Additionally, the primary activities are collapsed into one of twelve groups in a somewhat arbitrary manner. More

^{A38}In this section, we focus on the fragility of Card’s yearly models in his initial report (Document 419-141), not his yearly models in his rebuttal report (Document 419-143). The reason for this is that we were able to analyze the models in the initial report as part of a response, but we were not given the opportunity to respond to Card’s rebuttal report. While Card’s yearly models differ slightly across the two reports, all of his preferred models maintain the same faulty assumptions regarding the personal rating, race-disadvantaged interactions, and parental occupation. The other differences are less relevant for estimating the Asian American penalty.

^{A39}Similarly, AP exam scores are only available in the final two admission cycles. However, Card does not utilize these variables in his yearly regressions when they are available, despite the fact that admission is positively correlated with AP performance and Asian Americans take more AP exams and score higher conditional on taking the exams (see Table B.3.1 of Document 415-9). By choosing to exclude AP exams and scores, Card is biasing the Asian American penalty towards zero. Note their exclusion in earlier admissions cycles is not a choice, but is still likely to result in an estimated Asian American penalty that is biased towards zero.

importantly, the level of participation of the activity is done only for the work category, where total work hours are calculated over the course of the applicant’s high school career. This distorts the analysis in two ways. First, it overemphasizes the weight that work is given in the process, as work activities are only the eighth most popular activity listed for whites.^{A40} Second, white applicants work significantly more hours than Asian American applicants. Yet there are many activities where Asian American applicants invest substantially more hours than white applicants.

As a result, when we investigate the robustness of the yearly models, we consider two cases. First, we look at the case where we take the extracurricular activities defined by Card at face value. Second, we define our own set of extracurricular controls. We use the original 29 activity categories when constructing indicators for each of the first two listed activities. Instead of using the total hours of work over the course of the applicant’s high school career, we consider broader groupings of categories and measure participation both by counting the number of grades in which the applicant participated in each activity and indicating whether the applicant’s total accumulated hours in a category was above the median for those who had any positive hours in the category. Making these adjustments more precisely accounts for the impact of extracurricular activities on admissions decisions.

Similar to the pooled model robustness exercise, we are interested in whether a finding of an insignificant Asian American penalty using Card’s baseline yearly model is robust to: (i) inclusion of the personal rating; (ii) the exclusion of interactions between race and disadvantaged status; and (iii) inclusion of parental occupation. Appendix Table F13 indicates that the finding of no Asian American penalty is not robust. In the first column we present the estimated Asian American penalty when we employ the extracurricular variables as constructed by Card. The marginal effects reported are a weighted average of the year-specific estimates. We find that the magnitude of the estimated penalty in the yearly model is similar to the pooled model when we interact race and disadvantage. However, the result is not statistically significant. Excluding the personal rating or parental occupation leads to a large and statistically significant Asian American penalty. In the second column, we estimate Card’s yearly model, but use the corrected extracurricular measures. In this case,

^{A40}See Document 419-141 Appendix D, Exhibit 66.

the Asian American penalty is statistically significant when any of (i)–(iii) are addressed. The final column of the table are the results from the pooled specification and show that the estimated magnitude of the penalty is largely unaffected by moving to the yearly model.

The weighted averages reported in Appendix Table F13 mask important heterogeneity in the size and significance of the Asian American penalty across admissions cycles. In Appendix Table F14 we provide the year-by-year estimates of the Asian American penalty for Card’s baseline specification, as well as the robustness checks related to disadvantaged status, the personal rating, and parental occupation. In all models we use the extracurricular variables as defined by Card. For every specification, the estimated penalty is negative in all years except 2019. This pattern is interesting since this is the only admissions cycle to occur after the SFFA lawsuit was filed. The final row of the table reports the average marginal effect across admissions cycles excluding 2019. Here we find that, even when we add to the baseline model race interacted with disadvantaged status, the Asian American penalty is large and statistically significant. When we make all the model adjustments and exclude 2019, the Asian American penalty is 20% larger than in the corresponding yearly specification including 2019 (-0.90 from row (5) from Table F13).

This section has shown that being able to find no significant Asian American penalty among typical applicants to Harvard requires making a number of questionable modeling choices. If any of these decisions are reversed, a statistically significant Asian American penalty appears. This lack of robustness is in sharp contrast to our preferred specification, where altering many of the modeling choices does not alter the main finding.

Online Appendix References

- Arcidiacono, Peter. 2005. “Affirmative Action in Higher Education: How do Admission and Financial Aid Rules Affect Future Earnings?” *Econometrica* 73 (5):1477–1524. 17, 25
- Arcidiacono, Peter, Josh Kinsler, and Tyler Ransom. 2019. “Recruit to Reject? Harvard and African American Applicants.” Working paper, Duke University.
- . 2022. “Legacy and Athlete Preferences at Harvard.” *Journal of Labor Economics* 40 (1):133–156. 2, 8, 12, 15, 23, 25, A16
- Document 415-8. 2017. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL <https://docs.justia.com/cases/federal/district-courts/massachusetts/madce/1:2014cv14176/165519/415/1.html>. Plaintiff Expert Witness Opening Report. 7, 10, 22, 24, 26, A16, A31
- Document 415-9. 2018. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL <https://docs.justia.com/cases/federal/district-courts/massachusetts/madce/1:2014cv14176/165519/415/2.html>. Plaintiff Expert Witness Rebuttal Report. 6, 12, 17, 19, 21, 22, 24, 27, 36, 37, 38, 39, 40, 41, 42, A15, A16, A17, A18, A31, A35
- Document 419-141. 2017. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL https://projects.iq.harvard.edu/files/diverse-education/files/expert_report_-_2017-12-15_dr._david_card_expert_report_updated_confid_designs_redacted.pdf. Defendant Expert Witness Opening Report. 5, A31
- Document 419-143. 2018. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL https://projects.iq.harvard.edu/files/diverse-education/files/expert_report_rebuttal_as_filed_d._mass._14-cv-14176_dckt_000419_037_filed_2018-06-15.pdf. Defendant Expert Witness Rebuttal Report. 23, A31
- Document 421-9. 2017. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL https://www.courtlistener.com/recap/gov.uscourts.mad.165519/gov.uscourts.mad.165519.421.9_7_1.pdf. Deposition of William Fitzsimmons. 13, 23, A31
- Document 672. 2019. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL https://www.courtlistener.com/recap/gov.uscourts.mad.165519/gov.uscourts.mad.165519.672.0_2.pdf. Findings of Fact and Conclusion of Law.
- Trial Exhibit DX 016. 2018. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL <https://github.com>.

- [com/tyleransom/SFFAvHarvard-Docs/blob/master/TrialExhibits/D016.pdf](https://github.com/tyleransom/SFFAvHarvard-Docs/blob/master/TrialExhibits/D016.pdf). Harvard Reading Procedures for Class of 2017.
- Trial Exhibit DX 024. 2018. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL <https://github.com/tyleransom/SFFAvHarvard-Docs/blob/master/TrialExhibits/D024.pdf>. 2012 Casebook Discussion Guide. A31
- Trial Exhibit DX 680. 2018. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL <https://github.com/tyleransom/SFFAvHarvard-Docs/blob/master/TrialExhibits/D680.pdf>. Primary extracurricular activity by race. A31
- Trial Exhibit P001. 2018. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL <https://github.com/tyleransom/SFFAvHarvard-Docs/blob/master/TrialExhibits/P001.pdf>. Harvard Reading Procedures for Class of 2018. 7, 8, 18, 23, A19, A31
- Trial Exhibit P009. 2018. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL <https://github.com/tyleransom/SFFAvHarvard-Docs/blob/master/TrialExhibits/P009.pdf>. Office of Institutional Research report, “Admissions Part II: Subtitle”. 4, A31
- Trial Exhibit P028. 2018. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL <https://github.com/tyleransom/SFFAvHarvard-Docs/blob/master/TrialExhibits/P028.pdf>. Office of Institutional Research report, “Demographics of Harvard College Applicants”. 4, 16, A31
- Trial Exhibit P071. 2018. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL <https://github.com/tyleransom/SFFAvHarvard-Docs/blob/master/TrialExhibits/P071.pdf>. Harvard Reading Procedures for Class of 2019.
- Trial Exhibit P238. 2018. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL <https://github.com/tyleransom/SFFAvHarvard-Docs/blob/master/TrialExhibits/P238.pdf>. Email correspondence between admissions office personnel.
- Trial Exhibit P633. 2018. In *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College et al.* Civil Action No. 14-14176-ADB (D. Mass). URL <https://github.com/tyleransom/SFFAvHarvard-Docs/blob/master/TrialExhibits/P633.pdf>. Harvard Reading Procedures for Class of 2023. 7, A19, A31

F Supporting Figures and Tables

Table F1: List of *SFFA v. Harvard* Legal Documents Used

Document	Description
Document 415-8	Plaintiff’s expert witness opening report
Document 415-9	Plaintiff’s expert witness rebuttal report
Document 419-141	Defendant’s expert witness opening report
Document 419-143	Defendant’s expert witness rebuttal report
Document 419-1	Deposition of Harvard Admissions Director Marlyn McGrath
Document 421-9	Deposition of Harvard Admissions Dean William Fitzsimmons
Trial Exhibit DX 016	Class of 2017 application reading procedures
Trial Exhibit DX 024	Class of 2012 casebook discussion guide
Trial Exhibit DX 042	Demographic breakdown of applicants, admits and matriculants
Trial Exhibit DX 680	Table of primary extracurricular activities by race
Trial Exhibit P001	Class of 2018 application reading procedures
Trial Exhibit P009	Harvard Office of Institutional Research (OIR) report
Trial Exhibit P028	Harvard OIR report on admissions
Trial Exhibit P071	Class of 2019 application reading procedures
Trial Exhibit P164	“One-pager” for Class of 2018
Trial Exhibit P238	Email correspondence between admissions office personnel
Trial Exhibit P555	Office for Civil Rights Report (1990)
Trial Exhibit P621	Ratings frequencies for baseline sample
Trial Exhibit P633	Class of 2023 application reading procedures
Day 4 Trial Transcript	Transcript of Day 4 of trial
Day 14 Trial Transcript	Transcript of Day 14 of trial
Document 672	Trial court judge’s ruling

Table F2: Share Receiving a 2 or Better on Academic and Extracurricular Ratings by Academic Index Decile and Race

Decile	White	African American	Hispanic	Asian American
<i>Panel A: Academic Rating</i>				
1	0.11	0.02	0.03	0.00
2	0.41	0.08	0.05	0.54
3	1.91	0.96	0.68	1.36
4	9.14	6.07	4.45	7.98
5	26.26	23.08	17.04	26.36
6	50.19	48.43	43.83	51.08
7	68.37	68.54	64.28	71.46
8	82.73	80.37	79.63	86.16
9	93.30	93.37	91.47	95.12
10	97.16	94.70	95.26	98.08
Average	45.32	9.18	16.75	60.21
<i>Panel B: Extracurricular Rating</i>				
1	11.41	9.02	9.27	12.97
2	16.35	13.75	12.73	15.99
3	20.14	18.86	15.86	18.57
4	22.02	23.27	18.74	21.59
5	23.83	22.85	20.65	23.67
6	25.08	26.38	23.31	25.51
7	26.64	27.42	27.61	28.34
8	27.31	27.91	24.63	29.78
9	30.45	32.65	28.94	34.92
10	33.04	38.64	29.21	37.98
Average	24.38	15.56	16.84	28.27

Source: Authors' calculations from data presented in Table 5.4R of [Document 415-9](#). Data restricted to non-ALDC applicants from the Classes of 2014–2019.

Notes: Portions of this table also appear in [Arcidiacono, Kinsler, and Ransom \(2019\)](#) as Table 5.

Table F3: Share Receiving a 2 or Better on Personal and Alumni Personal Ratings by Academic Index Decile and Race

Decile	White	African American	Hispanic	Asian American
<i>Panel A: Personal Rating</i>				
1	8.11	9.49	8.48	8.01
2	12.58	15.75	13.16	12.91
3	16.25	23.35	17.77	13.46
4	18.62	28.95	20.39	14.24
5	20.40	33.89	25.60	15.69
6	22.72	35.04	28.41	16.46
7	22.59	40.00	30.03	18.11
8	26.10	39.57	32.20	17.93
9	28.23	40.31	30.24	20.87
10	29.62	46.97	34.21	22.20
Average	21.29	19.01	18.69	17.65
<i>Panel B: Alumni Personal Rating</i>				
1	26.33	30.96	26.29	28.13
2	33.72	39.83	33.42	32.03
3	39.77	46.84	38.59	36.35
4	44.27	55.56	43.86	40.66
5	48.43	59.98	50.32	44.24
6	51.84	62.20	54.50	46.96
7	54.08	69.89	56.90	51.93
8	58.20	67.48	62.44	53.78
9	62.20	70.92	62.89	57.46
10	64.98	73.48	71.05	63.61
Average	49.79	42.79	41.25	50.21

Source: Authors' calculations from data presented in Table 5.6R of [Document 415-9](#). Those with missing ratings are excluded from the calculations. Data restricted to non-ALDC applicants from the Classes of 2014-2019.

Notes: Portions of this table also appear in [Arcidiacono, Kinsler, and Ransom \(2019\)](#) as Table 5.

Table F4: Share Receiving a 2 or Better on School Support Ratings by Academic Index Decile and Race

Decile	White	African American	Hispanic	Asian American
<i>Panel A: Teacher 1 Rating</i>				
1	7.76	7.75	8.85	7.41
2	13.42	13.97	13.87	14.18
3	19.00	19.38	20.03	16.98
4	23.87	25.06	23.60	21.03
5	26.39	29.65	30.19	23.00
6	32.41	36.42	31.94	26.59
7	34.64	40.22	35.62	30.22
8	39.72	46.63	37.68	33.09
9	44.92	47.45	43.60	39.73
10	50.17	55.30	49.47	46.64
Average	30.46	17.15	21.60	30.84
<i>Panel B: Teacher 2 Rating</i>				
1	6.20	5.46	6.42	6.55
2	10.24	11.50	11.00	11.69
3	15.46	16.98	17.77	13.80
4	21.21	22.41	20.81	18.01
5	23.31	31.55	25.54	20.26
6	27.53	35.43	28.97	24.29
7	31.04	35.06	32.77	26.18
8	36.66	39.88	37.32	29.67
9	41.47	42.86	38.59	36.15
10	47.11	50.76	49.74	41.90
Average	27.16	14.83	18.86	27.44
<i>Panel C: Counselor Rating</i>				
1	4.64	4.88	5.72	5.76
2	8.99	10.86	10.15	9.19
3	14.49	16.72	14.83	12.25
4	18.49	20.31	17.32	14.93
5	22.06	26.42	21.06	17.84
6	25.59	32.87	25.26	22.61
7	29.24	35.73	30.35	24.96
8	34.39	38.04	34.15	27.69
9	39.16	43.88	34.32	33.88
10	44.63	49.24	45.00	38.34
Average	25.29	13.86	16.49	25.16

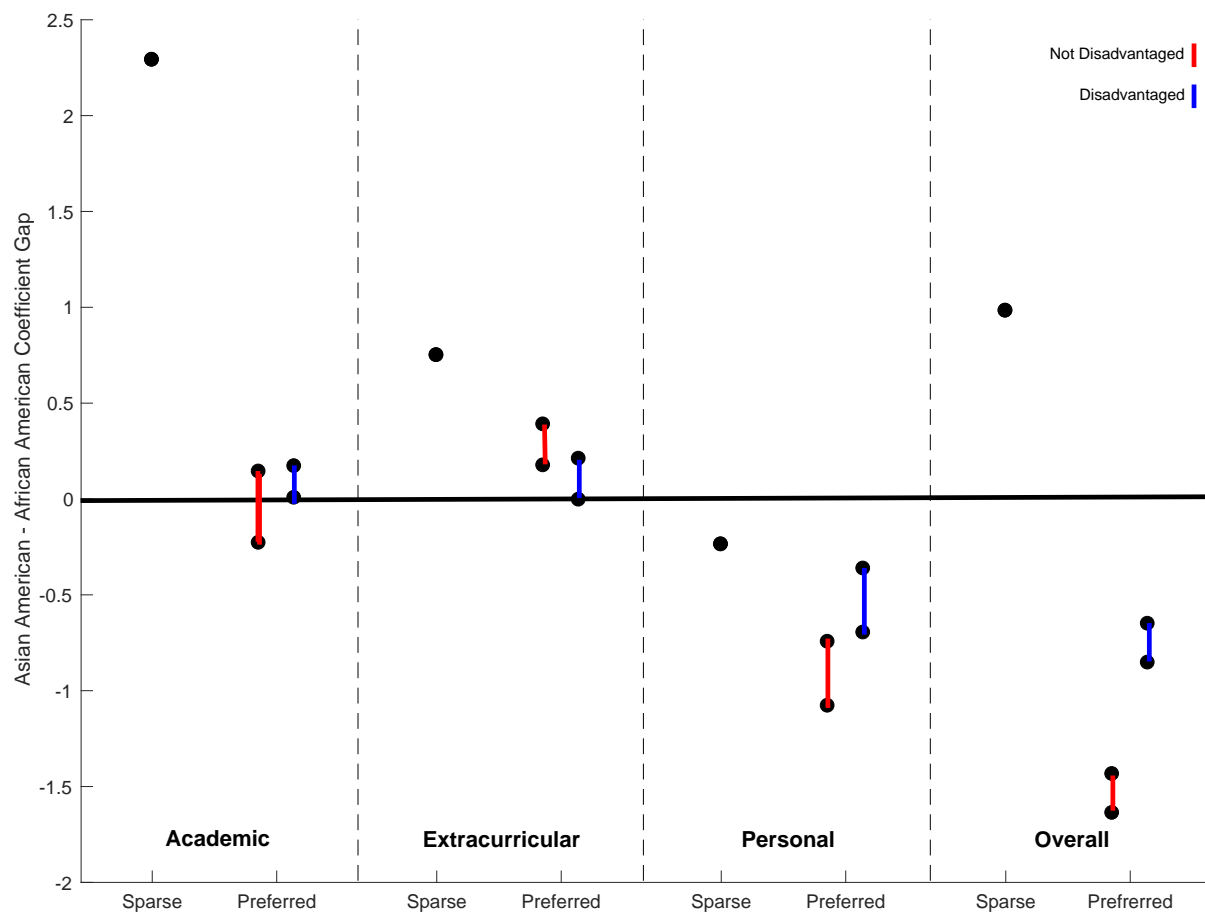
Source: Authors' calculations from data presented in Table 5.5R of [Document 415-9](#). Those with missing ratings are excluded from the calculations. Data restricted to non-ALDC applicants from the Classes of 2014–2019.

Table F5: Admission Rates of Applicants by LDC Status, Race, and Academic Index Decile

Decile	White		African American		Hispanic		Asian American		Total	
	Typical	LDC	Typical	LDC	Typical	LDC	Typical	LDC	Typical	LDC
1	0.00	6.32	0.03	3.19	0.00	0.00	0.00	6.29	0.01	5.27
2	0.39	12.20	1.03	6.61	0.32	11.54	0.20	7.16	0.53	10.47
3	0.56	16.67	5.19	25.36	1.95	8.15	0.64	11.53	1.65	15.56
4	1.82	22.62	12.76	39.94	5.50	30.20	0.86	23.90	3.29	23.72
5	2.57	26.18	22.41	48.92	9.13	42.45	1.86	21.28	4.40	28.39
6	4.20	31.85	29.72	54.73	13.65	41.46	2.49	29.78	5.64	33.70
7	4.79	36.04	41.12	82.43	17.28	48.49	3.98	40.45	6.61	38.51
8	7.53	47.49	44.48	75.01	22.93	49.85	5.12	53.17	8.22	47.66
9	10.77	56.94	54.59	99.90	26.16	43.98	7.55	56.45	10.40	56.67
10	15.27	57.07	56.06	83.43	31.32	95.10	12.69	63.02	14.58	60.64
Total	4.90	33.47	7.58	27.52	6.16	34.73	5.14	36.75	5.46	33.73

Source: Authors' calculations from data presented in Tables 5.1R, 5.2R, B.5.1R and B.5.2R of [Document 415-9](#).

Figure F1: Estimated Ratings Gaps between Asian Americans and African Americans with Varying Number of Controls



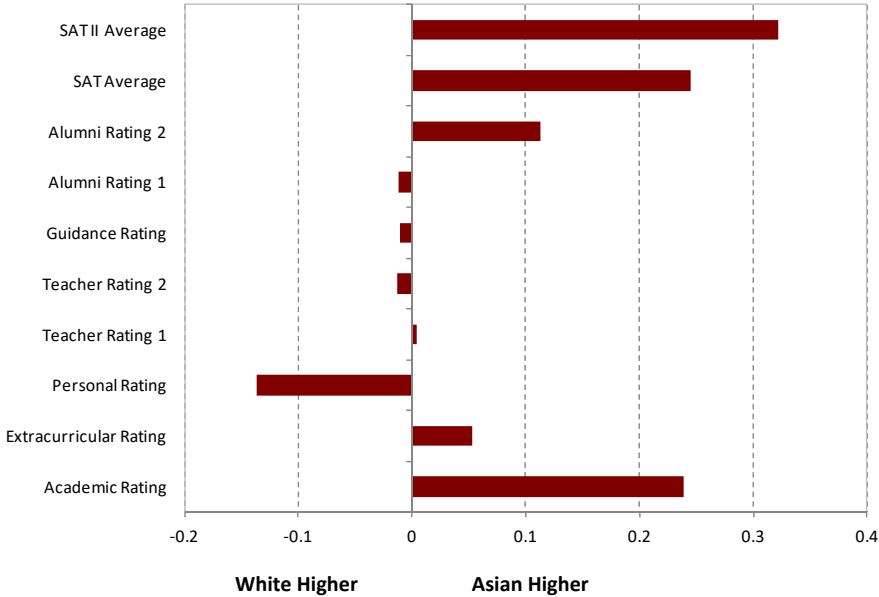
A36

Source: Authors' calculations from results reported in Appendix Tables F6 and F7.

Notes: Dots indicate coefficient estimates for a given rating and specification. Intervals represent the range between men and women by disadvantaged status. "Sparse" refers to a model with relatively few covariates (i.e. Model 1 in the results of Document 415-9); "Preferred" means the preferred model (i.e. Model 5 in the results of Document 415-9).

Figure F2: Harvard OIR Analysis of White and Asian American Applicants

Difference in Average Test Scores and Ratings for White and Asian Applicants



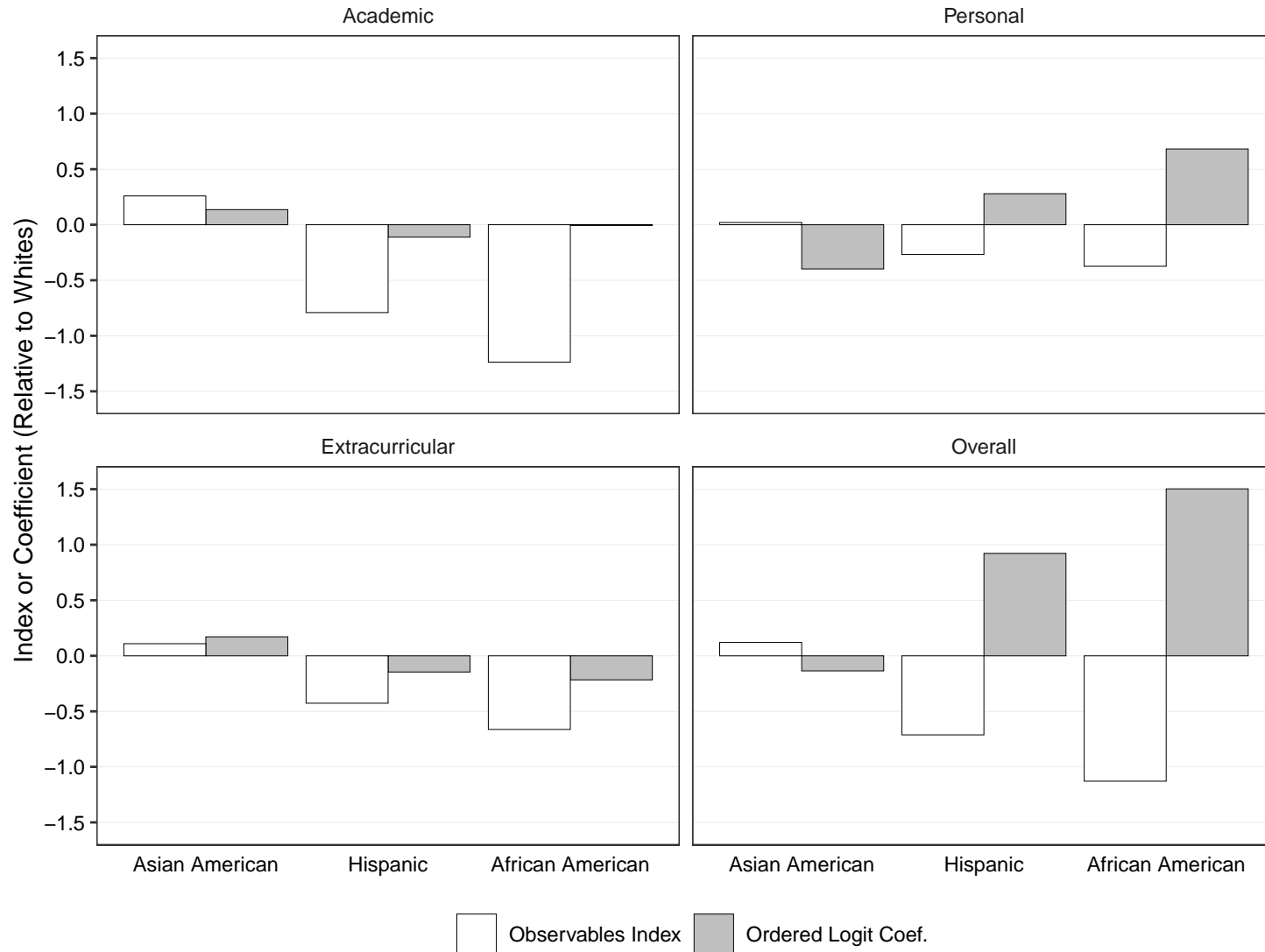
Notes:

- Excludes legacies and athletes.
- OIR doesn't have all ratings for all years, so number of applicants differs for each rating/test score.
- Differences are in standard deviations.

A37

Source: Page 5 of [Trial Exhibit P009](#) (report of Harvard's Office of Institutional Research).

Figure F3: Race Coefficients and Observable Indices by Harvard Ratings



Source: Authors' calculations from Table B.6.11R of [Document 415-9](#).

Notes: "Observables Index" refers to the predicted linear index of observables (i.e. $X_i \hat{\gamma}^R$) after removing race and year effects. "Ordered Logit Coef." refers to the coefficient on race from the ordered logit model of the given Harvard rating.

Table F6: Academic, Extracurricular, and School Support Ratings, Selected Coefficients

	Academic		Extracurricular		Teacher 1		Teacher 2		Counselor	
	Sparse	Preferred	Sparse	Preferred	Sparse	Preferred	Sparse	Preferred	Sparse	Preferred
African American	-1.685 (0.019)	-0.006 (0.043)	-0.503 (0.023)	-0.217 (0.044)	-0.606 (0.024)	0.012 (0.048)	-0.551 (0.026)	0.104 (0.051)	-0.577 (0.026)	0.164 (0.052)
Hispanic	-0.944 (0.017)	-0.112 (0.037)	-0.302 (0.021)	-0.146 (0.036)	-0.289 (0.021)	-0.023 (0.037)	-0.256 (0.023)	0.024 (0.039)	-0.289 (0.023)	0.017 (0.040)
Asian American	0.614 (0.014)	0.136 (0.031)	0.246 (0.015)	0.171 (0.026)	-0.048 (0.015)	-0.159 (0.026)	-0.086 (0.016)	-0.203 (0.028)	-0.054 (0.016)	-0.095 (0.028)
Missing	0.318 (0.023)	0.082 (0.051)	0.133 (0.025)	0.077 (0.043)	-0.015 (0.025)	-0.080 (0.043)	-0.063 (0.026)	-0.115 (0.046)	-0.048 (0.027)	-0.116 (0.047)
Female	-0.272 (0.011)	0.116 (0.034)	0.207 (0.012)	0.021 (0.031)	-0.001 (0.012)	0.093 (0.032)	-0.027 (0.013)	0.085 (0.035)	0.032 (0.013)	0.034 (0.035)
Disadvantaged	0.131 (0.020)	0.048 (0.046)	0.372 (0.024)	0.202 (0.045)	0.430 (0.024)	0.188 (0.045)	0.453 (0.026)	0.278 (0.048)	0.451 (0.026)	0.168 (0.049)
Female X African American		0.097 (0.045)		0.216 (0.046)		-0.068 (0.051)		-0.096 (0.056)		-0.012 (0.056)
Female X Hispanic		-0.051 (0.042)		0.079 (0.042)		0.007 (0.044)		-0.053 (0.047)		0.003 (0.048)
Female X Asian American		-0.068 (0.037)		0.002 (0.031)		0.033 (0.031)		0.056 (0.034)		0.000 (0.034)
Female x Missing		-0.066 (0.063)		0.010 (0.053)		0.006 (0.054)		0.062 (0.057)		0.098 (0.059)
Disadv X African American		-0.120 (0.061)		0.106 (0.062)		0.122 (0.066)		-0.053 (0.072)		0.009 (0.072)
Disadv X Hispanic		-0.262 (0.060)		0.076 (0.060)		0.093 (0.061)		-0.033 (0.066)		0.186 (0.068)
Disadv X Asian American		-0.092 (0.061)		-0.073 (0.057)		0.017 (0.057)		0.002 (0.061)		0.126 (0.062)
Disadv X Missing		-0.008 (0.111)		0.020 (0.103)		0.041 (0.104)		-0.075 (0.112)		-0.128 (0.116)
Observations	142728	136208	142728	136208	136958	130733	115618	110195	134341	128288
Pseudo R Sq.	0.161	0.565	0.041	0.128	0.03	0.142	0.029	0.137	0.046	0.185
Major, Dockets, Waiver, Early Academics, Nbhd/School, Ratings	Y N	Y Y	Y N	Y Y	Y N	Y Y	Y N	Y Y	Y N	Y Y

Source: Tables B.6.1R and B.6.2R of Document 415-9. Data restricted to non-ALDC applicants from the Classes of 2014–2019.

Notes: Standard errors below each coefficient in parentheses. “Sparse” means a model with relatively few covariates (Model 1 in the tables in Document 415-9); “Preferred” means the preferred model (Model 5 in the tables in Document 415-9).

Table F7: Personal and Overall Ratings, Selected Coefficients

	Personal		Alumni Personal		Overall		Alumni Overall	
	Sparse	Preferred	Sparse	Preferred	Sparse	Preferred	Sparse	Preferred
African American	-0.108 (0.025)	0.682 (0.053)	-0.132 (0.021)	0.236 (0.041)	-0.821 (0.019)	1.503 (0.038)	-0.664 (0.020)	0.126 (0.040)
Hispanic	-0.075 (0.023)	0.279 (0.044)	-0.111 (0.019)	0.062 (0.034)	-0.237 (0.016)	0.922 (0.030)	-0.358 (0.019)	0.001 (0.033)
Asian American	-0.346 (0.018)	-0.398 (0.034)	-0.010 (0.014)	-0.181 (0.025)	0.160 (0.012)	-0.136 (0.022)	0.232 (0.014)	0.160 (0.024)
Missing	-0.237 (0.029)	-0.347 (0.056)	0.019 (0.023)	-0.129 (0.041)	0.095 (0.020)	-0.086 (0.036)	0.187 (0.023)	0.165 (0.040)
Female	0.170 (0.014)	0.161 (0.039)	0.177 (0.011)	0.240 (0.032)	-0.017 (0.010)	0.117 (0.027)	-0.027 (0.011)	-0.094 (0.031)
Disadvantaged	0.754 (0.026)	0.553 (0.052)	0.172 (0.022)	-0.075 (0.044)	0.603 (0.019)	0.743 (0.038)	0.191 (0.021)	0.068 (0.043)
Female X African American		-0.239 (0.057)		-0.066 (0.045)		-0.163 (0.040)		-0.085 (0.044)
Female X Hispanic		-0.015 (0.051)		-0.021 (0.041)		-0.013 (0.035)		-0.014 (0.040)
Female X Asian American		0.095 (0.040)		0.053 (0.031)		0.040 (0.026)		-0.062 (0.030)
Female x Missing		0.118 (0.069)		0.034 (0.054)		0.011 (0.045)		-0.041 (0.052)
Disadv X African American		-0.324 (0.073)		0.101 (0.061)		-0.684 (0.053)		-0.066 (0.059)
Disadv X Hispanic		-0.048 (0.070)		0.174 (0.060)		-0.353 (0.051)		-0.077 (0.058)
Disadv X Asian American		0.058 (0.067)		0.087 (0.056)		0.100 (0.048)		-0.060 (0.054)
Disadv X Missing		0.068 (0.123)		0.078 (0.101)		-0.155 (0.088)		-0.071 (0.098)
Observations	142728	136208	111524	108054	142701	136183	111524	108054
Pseudo R Sq.	0.06	0.289	0.012	0.341	0.059	0.331	0.035	0.375
Major, Dockets, Waiver, Early	Y	Y	Y	Y	Y	Y	Y	Y
Academics, Nbhd/School, Ratings	N	Y	N	Y	N	Y	N	Y

Source: Tables B.6.3R and B.6.4R of Document 415-9. Data restricted to non-ALDC applicants from the Classes of 2014-2019.

Notes: Standard errors below each coefficient in parentheses. “Sparse” means a model with relatively few covariates (Model 1 in the tables in Document 415-9); “Preferred” means the preferred model (Model 5 in the tables in Document 415-9).

Table F8: The Role of Observed and Unobserved Factors in Racial/Ethnic Differences in Component Scores

	Overall	Academic	Extra-curricular	Teacher 1	Teacher 2	Counselor	Alumni Personal	Alumni Overall	Alumni Personal
<i>Average Index Z-score (relative to White)</i>									
African American	-1.129	-1.237	-0.663	-0.759	-0.722	-0.849	-0.253	-0.637	-0.374
Hispanic	-0.712	-0.791	-0.427	-0.451	-0.415	-0.514	-0.191	-0.421	-0.268
Asian American	0.120	0.259	0.109	0.142	0.116	0.049	0.027	0.073	0.020
<i>Coefficients (White is normalized to zero)</i>									
African American	1.503	-0.006	-0.217	0.012	0.104	0.164	0.236	0.126	0.682
Hispanic	0.922	-0.112	-0.146	-0.023	0.024	0.017	0.062	0.001	0.279
Asian American	-0.136	0.136	0.171	-0.159	-0.203	-0.095	-0.181	0.160	-0.398

Source: Table B.6.11R of [Document 415-9](#).

Notes: The average index Z-score is calculated by taking the variables in the preferred ratings models absent race and admissions cycle and multiplying them by their corresponding coefficients from the ratings models. Then, the mean for white applicants is subtracted and we divide by the standard deviation. Finally, we take the averages for each racial group (note that mechanically this is zero for whites). Coefficients refer to the base race coefficients in the ratings models.

Table F9: Predicted and Actual Asian American Admit Rates by Admission Index Decile

Decile	Distribution of Latent Admissions Index			
	Actual	Normal	Flexible	Log-normal
Bottom 5	0.04	0.05	0.04	0.77
6	0.32	0.34	0.33	1.28
7	0.77	0.79	0.76	1.7
8	2.03	2.10	2.03	2.6
9	7.01	6.97	7.01	5.56
10	41.68	41.69	41.68	41.87

Notes: Actual refers to Table 9.1 of [Document 415-9](#). Decile refers to the decile of the Asian American admissions index. Normal and Log-normal refers to the distribution of the admissions index. Flexible uses a normal distribution as well as the following transformations of the normal distribution: the square, the square interacted with the value being above zero, and the exponential. We obtained by Method of Simulated Moments the weights on these transformations that match to the actual distribution.

Table F10: Mother's and father's occupations vary in non-credible ways

	Admissions Class					
	2014	2015	2016	2017	2018	2019
<i>Mother's Occupations</i>						
Other	1266	4703	4339	4280	5666	5958
Homemaker	3476	4292	3967	4042	4629	3847
Unemployed	1449	2350	2274	2360	10	9
Low Skill.	1097	37	18	12	24	20
Self-Employed	0	991	989	928	1076	1138
<i>Father's Occupations</i>						
Other	1593	4608	4268	4587	4941	5663
Homemaker	44	56	50	61	101	71
Unemployed	963	1493	1390	1300	5	8
Low Skill.	1098	42	33	34	15	27
Self-Employed	0	2134	2148	2108	2335	2432

Source: Data presented in Table 3.2N of [Document 415-9](#).

Notes: Construction of occupation categories described in [Document 419-143](#).

Table F11: Intended Career varies in non-credible ways

	Admissions Class					
	2014	2015	2016	2017	2018	2019
Academic	1,723	25	19	15	2,247	13
Arts	846	331	321	284	390	283
Business	2,189	2,385	2,486	2,556	1,918	2,906
Communications	695	741	634	528	229	491
Design	283	161	131	101	82	105
Government	1,604	1,785	1,695	1,683	1,610	1,617
Health	234	95	85	107	4,944	96
Law	2,093	1,963	1,787	1,639	708	1,484
Library	63	0	0	0	0	0
Medicine	6,254	6,185	5,879	5,863	3	5,977
Religion	42	2	0	1	0	0
Science	3,268	5,242	5,437	5,519	9,182	7,394
Trade	2	7	8	7	6	9
Social Service	339	41	51	47	0	52
Teaching	167	660	598	598	17	514
Other	445	1,275	1,210	1,223	231	1,857
Undecided	1,821	5,022	4,614	4,887	3,537	3,661
Unknown	121	87	82	55	102	101
Total	22,189	26,007	25,037	25,113	25,206	26,560

Source: Data presented in Table B.4.1N of Document 415-9.

Table F12: Is a Pooled Model that finds no Asian American Penalty Robust?

	Average Marginal Effect
(1) Baseline pooled model from Card	-0.22%
(2) Interact race and disadvantaged	-0.32%*
(3) White and Asian American applicants only	-0.34%*
(4) Non-disadvantaged applicants only	-0.35%*
(5) Exclude personal rating	-0.65%*
(6) Exclude parental occupation	-0.37%*
(7) Combine (2), (5), & (6)	-0.95%*

Source: Data presented in Table 4.1N of Document 415-9. *=statistically different from zero at the 95% level. Marginal effects are calculated without perfect predictions.

Notes: All models exclude ALDC applicants.

Table F13: Is a Yearly Model that finds no Asian American Penalty Robust?

	Yearly with Card extracurriculars	Yearly with corrected extracurriculars	Pooled
(1) Baseline model from Card	-0.18%	-0.24%	-0.22%
(2) Interact race and disadvantaged	-0.29%	-0.36%*	-0.32%*
(3) White and Asian American applicants only	-0.37%	-0.47%*	-0.34%*
(4) Non-disadvantaged applicants only	-0.29%	-0.37%*	-0.35%*
(5) Exclude personal rating	-0.56%*	-0.62%*	-0.65%*
(6) Exclude parental occupation	-0.39%*	-0.47%*	-0.37%*
(7) Combine (2), (5), & (6)	-0.90%*	-0.98%*	-0.95%*

Source: Data presented in Table 4.2N of Document 415-9. *=statistically different from zero at the 95% level. Marginal effects are calculated without perfect predictions.

Notes: All models exclude ALDC applicants.

Table F14: Yearly estimates of the Asian American Penalty

	(1)	(2)	(3)	(4)	(5)
	Card Baseline	Interact Disadvantaged	No Personal Rating	No Parental Occupation	(2), (3), and (4)
2014	-0.31%	-0.38%	-0.79%	-0.69%	-1.23%
2015	-0.33%	-0.41%	-0.74%	-0.60%	-1.07%
2016	-0.02%	-0.16%	-0.72%	-0.34%	-1.12%
2017	-0.23%	-0.30%	-0.34%	-0.32%	-0.64%
2018	-0.57%	-0.71%	-0.97%	-0.75%	-1.33%
2019	0.37%	0.22%	0.19%	0.34%	-0.03%
Avg. without 2019	-0.29%	-0.39%*	-0.71%*	-0.54%*	-1.08%*

Source: Data presented in Table 4.3N of Document 415-9. *=statistically different from zero at the 95% level. Marginal effects are calculated without perfect predictions.

Notes: All models exclude ALDC applicants.