PLAINTIFF'S
EXHIBIT
P518

REPLY EXPERT REPORT OF PETER S. ARCIDIACONO

Students for Fair Admissions, Inc. v. The United States Naval Academy, et al.

No. 23 Civ. 2699 (RDB)

Table of Contents

List of Figures

List of Tables

1 Executive Summary

In my opening report, I showed that race/ethnicity played a substantial role in admissions at USNA, with the preferences especially large for Black applicants. USNA's racial preferences are pervasive, manifesting themselves throughout the admissions process. Because none of USNA's expert reports included any analysis of USNA's admissions data and/or the role race plays in admissions, my rebuttal report explained how USNA's experts' limited statistical analysis is either weak or irrelevant to this case; how USNA's experts never address the fact that the benefits of diversity are context-specific and depend on how diversity is achieved; and how USNA's experts neglected to consider any of the costs of racial preferences.

USNA submitted an expert report on behalf of Stuart Gurrea, Ph.D. at the rebuttal stage. Notably, Doctor Gurrea's report indicates that he began work on it at least as far back as March of this year. He employed USNA admissions data that USNA produced for the first time in connection with his report, which included new analysis that was not in any sense a "rebuttal" because it was not responsive to my work in this case.

In any event, Doctor Gurrea's report does nothing to undermine my prior conclusions. He mischaracterizes the relevant econometric literature, proposes alternative modeling choices that actually show race as having an even larger effect on admissions than my model, and engages in econometric sleight of hand to try to mask the outsized effect that race has on admissions decisions at USNA. There are too many errors in his analysis for me to address them all here, but I do address the following in this supplemental report:

1. Doctor Gurrea criticizes my use of a logit model to evaluate USNA's admissions decisions, claiming that USNA's admissions decisions are dependent over time and arguing that makes them unsuitable for a logit model. But he is wrong about this and misunderstands the relevant literature. While USNA has rolling admissions, they are still evaluated according to a common standard, making admissions models that have been used in the literature appropriate and his interdependency concern irrelevant.

2. Next, Doctor Gurrea claims that my admissions model suffers from omitted variable bias. But his position is inconsistent with the literature on this subject. Perhaps more importantly, accounting for the variables he claims I omitted works against him—those

variables either make no difference to the magnitude of USNA's racial preferences or else show them to be even larger than I estimated.

3. Doctor Gurrea also criticizes my sample selection criteria; he says it would be better to exclude service-connected nominees from my admissions model. Employing his sample selection criteria results in *larger* estimates of USNA's racial preferences.

4. Tellingly, Doctor Gurrea does not propose any supposed better method of modeling USNA admissions, implying that according to him there is no way to evaluate USNA's claims and we just need to take their word for it. At the same time, his high-level description of the admissions process sharply conflicts with the Latta declaration.

5. Doctor Gurrea claims that my categorization of race/ethnicity is arbitrary and that his 'data-driven' categorization shows smaller effects. But his 'data-driven' way results in a model that fits the data worse (as he even concedes) primarily because of its poor predictions for those of multiple races/ethnicities. Regardless, his categorization still shows substantial racial preferences.

6. Doctor Gurrea's claim that a model with no controls for race has little effect on the accuracy of the model is misleading. It's an obvious attempt to mask the effect of USNA's racial preferences by spreading them across the entire admissions pool. Naturally, his no-racial-preferences model does a terrible job of predicting admissions for minority applicants, which only confirms that USNA employs large racial preferences in its admissions decisions.

7. Doctor Gurrea claims that race does not affect decisions regarding Qualified Alternates, but substantial statistical evidence demonstrates that race/ethnicity does play a role for those with scores below the highest observed QA threshold (precisely where one would expect it).

2 Doctor Gurrea makes a number of conceptual mistakes and mischaracterizes my analysis

2.1 Doctor Gurrea misunderstands when a logit model is appropriate

Doctor Gurrea makes the surprising argument that estimating a logit model of admissions is inappropriate in the context of USNA admissions. He does this by first asserting that logit models are inappropriate for choices that are dependent over time (Gurrea 90). Doctor Gurrea then argues that, because USNA seeks a diverse student body with a wide variety of backgrounds, decisions must be "dependent over time" (Gurrea 95), and that USNA has rolling admissions, which involves a time dimension (Gurrea 93). He adds that whether someone has already been admitted from one under-represented district may affect whether someone else from that district will be admitted under the auspices of a preference for variety (Gurrea 94). Nowhere does Doctor Gurrea propose an alternative estimation strategy, let alone estimate one that supposedly does a better job than a logit model. Regardless, as I illustrate below, the objections Doctor Gurrea raises are not relevant for my preferred model.

The arguments Doctor Gurrea offers for the inappropriateness of the logit model in this case are made in point 90 which I repeat in full here:

> The authoritative source on logit models that Dr. Arcidiacono cites is by Professor Kenneth Train. Professor Train explains that a logit model of choices over time assumes each choice is independent from other choices:
>
> "The assumption of independence also enters when a logit model is applied to sequences of choices over time. The logit model assumes that each choice is independent of the others. In many cases, one would expect that unobserved factors that affect the choice in one period would persist, at least somewhat, into the next period, inducing dependence among the choices over time." (Train 18)
>
> As a result, Professor Train warns about the use of the logit model in cases where the unobserved factors are correlated over time:
>
> "If unobserved factors are independent over time in repeated choice situations,

> then logit can capture the dynamics of repeated choice, including state dependence. However, logit cannot handle situations where unobserved factors are correlated over time." (Train 42)
>
> As to the reasonableness of assuming independent unobserved factors when choices are made over time, Dr. Train explains that:
>
> "Of course, the assumption of independent errors over time is severe. Usually, one would expect there to be some factors that are not observed by the researcher that affect each of the decision makers' choices. In particular, if there are dynamics in the observed factors, then the researcher might expect there to be dynamics in the unobserved factors as well." (Train 52)

As is clear from the relevant section of Professor Train's book,[1] the cases Professor Train has in mind are of the sort that some people have more of a preference for say, alcohol, and that preference will likely stick with them over time. The reason this is important is when the researcher is interested in habit persistence. When we see that one consumer consistently buys more alcohol than another consumer, does this reflect that consuming alcohol today makes one want to consume more alcohol tomorrow? Or does it reflect that some people just have unobserved differences in taste for alcohol that are unrelated to how much alcohol they have consumed in the past?

But this sort of concern holds little relevance for the unobserved factors in my admissions model and, to that the extent that it is relevant, is well captured by the observed factors in my models. What are the unobserved factors in my admissions model? Each admissions decision is made by reviewing a particular candidate's file. The quality of the candidate consists both of factors I control for in the model (such as components of the WPM) and factors that I do not (such as grades in individual high school courses). These latter factors make up what is meant by unobserved factors that Professor Train discusses. And it is completely reasonable to assume that these are independent across applicants.

Doctor Gurrea argues that there is a second set of unobserved factors that reflect the quality of who has been admitted so far (because of the rolling admissions) and quality of

[1]See Section 3.3.3, pages 50-52 of Train (2009).

the applicant pool in a particular year (both overall and within a particular district). Doctor Gurrea then argues that

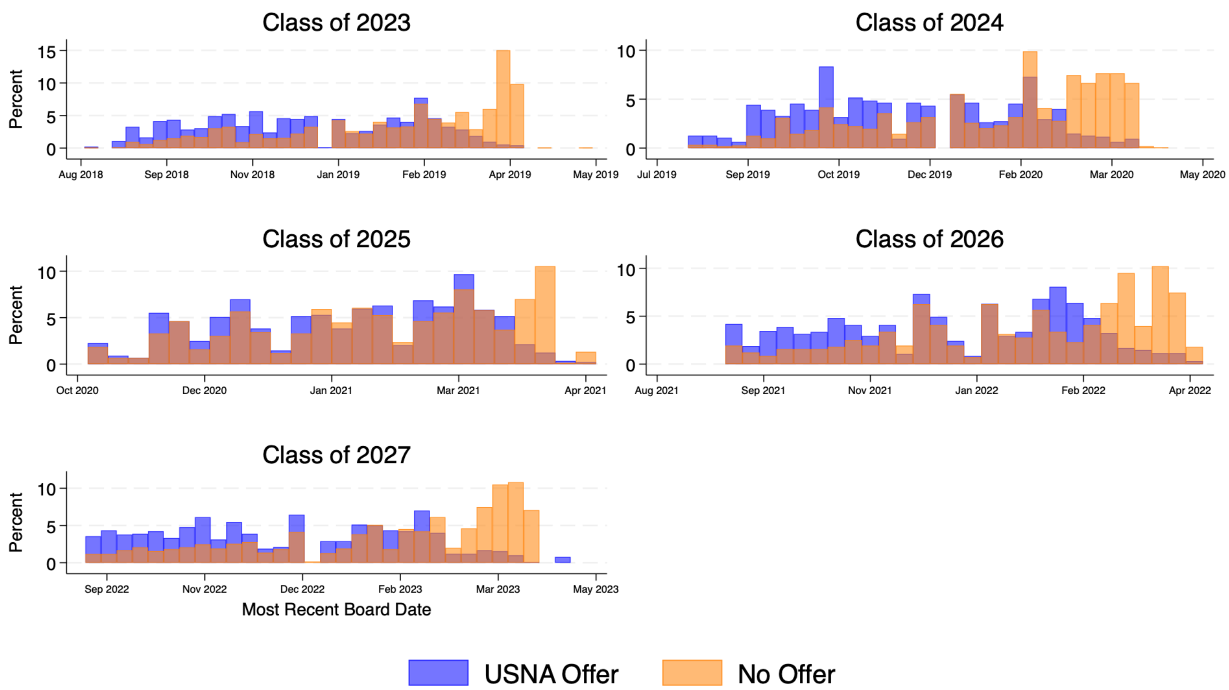
> "Because class size is fixed, the likelihood of being admitted is dependent on prior admissions decisions. For example, if a class has been filled, subsequent decisions will be impacted by the unavailability of appointments for additional applicants." (Gurrea 91)

This would be true if, when an applicant's file arrives, a final decision is made on every applicant. But if instead clear cases are resolved—e.g. strong applicants that USNA knows will be admitted regardless of when their applications arrived and weak candidates that USNA knows will be rejected regardless of the rest of the pool—and then more marginal cases are resolved later, then what cases have already been decided are irrelevant. Instead, what is relevant is the quality of the pool, both overall and on the slates for which the applicant is competing.

In supporting his argument, Doctor Gurrea produces a histogram of the most recent admissions board dates for applications submitted during the class of 2027 admissions cycle (Gurrea, Figure 1). Note that this is *not* when the applicant submits their application but rather the last time the board reviews their application. These data depict a relatively even distribution of application reviews up until the final month of the admissions cycle, when the number of reviews significantly increases. What is missing from his analysis is that timing of *admissions* decisions is significantly different from *rejection* decisions. To see this, I use data listed for Doctor Gurrea's analytical sample (see bottom row of Gurrea, Exhibit 4) and plot the last observed Board date for both those who were accepted and rejected for each of the five class years.

Figure 2.1F shows that, for each class, there is a spike in rejections at the end of the admissions cycle. This is consistent with USNA holding off on making decisions on marginal candidates until the end of the admissions cycle (as I note above). (Moreover, this is precisely why USNA—like many universities—has a waiting list: to push decisions on marginal candidates until the end.) Were admissions decisions truly interdependent, as Dr. Gurrea suggests, then we would not expect to see this same pattern hold each cycle—unless it

Figure 2.1F: Shares of USNA Admissions Offers and Rejections by Most Recent Board Date



Notes: Data are limited to medically and physically qualified applicants who completed their applications (i.e., have a board result), received nominations, had BGO interviews, are not blue chip athletes, and are not missing data for any WPM component. For 2023-2024, the field 'Result Meaning' is used for the most recent board result.

were the case that in every cycle USNA filled up its class too early, not recognizing that many strong candidates would be evaluated at the end of the cycle. This is, of course, nonsense. It would be ridiculous if applicants were rejected more often simply because the Board randomly decided to review some other applicant files first.

Now, invariably, as some admits decline their admissions offers, the admissions standard decreases. My model captures this with class-year effects that guarantee the predicted number of admissions in the model matches the number of admissions in the actual dataset every year. As a result, there is not a correlation between *unobserved* factors across applicants in an admissions cycle, but a correlation in *observed* factors which are the class-year effects. That is, those who apply in years where there is stiff competition will have lower chances of admission than when applying in years where the competition is weaker. This is precisely why I control for class-year effects.

2.2 Doctor Gurrea misunderstands the econometrics literature on selection on observables/ unobservables

Doctor Gurrea argues that my estimates of racial preferences are overstated as a result of omitted variable bias (Gurrea 98-101, 118-123), rather than being conservative estimates as I claim in my report (Gurrea 104). In my opening report, I showed that as additional observables were added, the effects of race–especially for Black students–increased for USNA admissions (Arcidiacono opening 61-64). Hence, consistent with a large literature on this subject, there was no reason to believe adding additional controls would reduce the magnitude of racial preferences. Rather, I would expect the estimated racial preferences to, if any thing, increase with additional controls.

Doctor Gurrea argues that I am misinterpreting the literature (Gurrea 105-106) and have violated the key conditions for the arguments from the literature to hold (Gurrea 107-108). Yet he (at best) misunderstands the relevant literature or (at worst) selectively lifts passages out of the literature without context that undermines his very point. Each of the papers I cited that were then quoted back to me by Doctor Gurrea (Altonji, Elder, and Taber 2005, Krauth 2016, and Oster, 2019) considers cases between selection on observables being the *same* as selection on unobservables and the selection on observables being *uncorrelated* with selection on unobservables. When I report the results of my admissions model, I am treating the observables as being uncorrelated with the unobservables. Allowing for a positive correlation between the observables and unobservables—as each of the papers Doctor Gurrea cites does—would yield race coefficients of even larger magnitude than my model estimates. The cautionary quotes that Doctor Gurrea cites are in reference to one extreme, which is assuming the selection operates in the same way on unobservables as it does on observables. But the other extreme the authors consider–the conservative one for my case–is the assumption that the observables are uncorrelated with the unobservables. *None* of these papers support the idea that selection on observables operate in the *opposite direction* as selection on unobservables, which is the only circumstance in which my models could have overestimated the effect of USNA's racial preferences on admissions decisions.

Further, in contrast to what Doctor Gurrea claims, there is even more statistical evidence here (compared to my work in the Harvard and UNC cases) supporting that my estimates of the magnitude of USNA's racial preferences is conservative. For both Harvard and UNC, I showed how the observables associated with admissions varied across racial groups, establishing that Hispanics and especially African Americans were significantly weaker than whites and Asian Americans on these observables, with Asian Americans stronger than whites at Harvard. I made the same statistical arguments from this data and the results were published with these claims.[2] I showed similar statistical findings to UNC and Harvard on pages 102-105 of my opening report.

What makes the statistical evidence stronger in this case is the auxiliary evidence on performance at USNA. Although Doctor Gurrea claims that I focus only on academic measures for this analysis (Gurrea 131), the Commandant's List is much more than an academic measure. Indeed, the academic benchmark for the Commandant's List is somewhat weak, requiring only a 2.9 grade point average for the semester. But the Commandant's list also requires strong ratings on aptitude, conduct, physical education, and physical readiness. If it were the case that I was somehow missing a factor that Black applicants were especially strong on and that was the driver behind their high admissions rates (given their observables), then I would expect some performance measure to reveal that to be the case, with Black midshipmen performing better than their observed characteristics would predict. Yet the data reveals the opposite: Black midshipmen, if anything, underperform relative to their observed characteristics.

[2] See, for example, Arcidiacono, Kinsler, Ransom (*Journal of Political Economy: Microeconomics* 2023).

3 Doctor Gurrea's alternative modeling choices are either misguided or would show USNA to have even larger racial preferences than my models indicate

Doctor Gurrea takes issue with a number of my choices regarding what the relevant sample is (Gurrea, 78) and which controls to include (Gurrea, 118-124). Given the issues he raises with my choices, and given that he created what he believes to be the more relevant sample, one would expect to see Doctor Gurrea actually estimate admissions models on his purportedly 'correct' sample and with, according to him, more appropriate controls. I found it quite curious that Doctor Gurrea never estimates an admissions model on his preferred sample and with the controls he criticizes me for omitting. In this section I show the likely reason why: estimating my models and making the adjustments Doctor Gurrea recommends shows USNA's racial preferences to be even *larger* than I concluded in my previous reports (3.1) and adding the controls he prefers either has no effect or increases the estimated racial preferences (3.2).

Doctor Gurrea also challenges how I categorize race/ethnicity (Gurrea 144-152). Doctor Gurrea proposes an alternative categorization that fits USNA's admissions decisions worse, especially for minority candidates. Further, this categorization tends to mask the size of racial/ethnic preferences, as under his categorization an applicant could receive an admissions boost for both their race and their ethnicity (3.3).

Doctor Gurrea next engages in econometric sleight of hand in challenging how important race is in USNA admissions (Gurrea 170). He removes racial preferences from the admissions model and reports that his model without race predicts admissions decisions with nearly the same level of accuracy as my model. From there, he argues that USNA's racial preferences must not have much effect on admissions decisions. But of course, this tactic obscures the effect of USNA's racial preferences by spreading them over the entire applicant pool (the vast majority of which do not receive racial preferences). What's more, had Dr. Gurrea showed the accuracy of this model for *minority* applicants (the actual population to which they apply), it would show that it does a terrible job of predicting minority admission—particularly for Black applicants—again underscoring my conclusion that racial preferences are enormous (3.4).

3.1 Using Doctor Gurrea's preferred sample *increases* the estimated effects of race

Doctor Gurrea essentially agrees with me regarding the relevant data set with one key difference: he argues that those being nominated from the military (i.e. service-connected nominees) should not be included in the model (Gurrea 78-79).[3] His rationale is that the admissions process operates differently for this group of applicants. While I believe my preferred model handles these applications well given the rich set of controls regarding, for example, the types of nominations applicants receive, it is straightforward to estimate my admissions models without this group.

Column (1) of Table 3.1F shows results using my preferred model in my rebuttal report.[4] Column (2) of Table 3.1F reveals what Doctor Gurrea declined to show– that when my preferred model is estimated incorporating the key sample changes he proposes, *each of the race coefficients increases* (with the Black coefficient rising to 3.16). The fact that Doctor Gurrea's preferred sample shows even stronger effects of race further demonstrates that my estimates were conservative.

Doctor Gurrea also claims that I "failed to consider the impact of a candidate belonging to an underrepresented district, which is an observable relevant factor for admission." (Gurrea 108). If belonging to an underrepresented congressional district were an identified variable in the dataset (i.e., an observable), I would have expected Doctor Gurrea to show analysis of this variable and how my model is inaccurate for those districts. I am not aware of this variable existing in the data and Doctor Gurrea's replication package did not reveal this variable (or any indictor variable he might have created to reflect an underrepresented

[3]The other difference Gurrea mentions is that he removes applicants with no board ratings. This affects four observations after employing the other restrictions and so has virtually no effect on the analysis.

[4]The full set of coefficients is presented in Appendix Table 3.1F. As explained in my rebuttal report, my preferred model includes a dummy variable that accounts for cases where the reported SAT score is a placeholder. Having accounted for this placeholder issue, my preferred model yields a Black coefficient of 2.96, which is slightly higher than in my original report. Doctor Gurrea was aware of the placeholder SAT issue (Gurrea 43) but chose not to correct it in any of the estimation models he estimated. In fact, Doctor Gurrea was aware of this through a telephone call on March 12th (Gurrea, footnote 49, page 8 of Appendix I).

Table 3.1F: Logit Estimates of USNA Admissions, My Preferred Model vs Dr. Gurrea's Suggestions

	Model 1	Model 2	Model 3	Model 4
Asian	1.449***	1.523***	1.520***	1.297***
	(0.090)	(0.093)	(0.093)	(0.096)
Black	2.958***	3.155***	3.152***	3.307***
	(0.134)	(0.140)	(0.140)	(0.147)
Declined/Missing	0.001	0.000	0.000	-0.002
	(0.222)	(0.232)	(0.232)	(0.238)
Hispanic	1.195***	1.238***	1.238***	1.213***
	(0.091)	(0.094)	(0.095)	(0.098)
Native American / Hawaiian	1.237***	1.261***	1.271***	1.340***
	(0.190)	(0.196)	(0.196)	(0.206)
Female=1	0.329***	0.349***	0.350***	0.198***
	(0.066)	(0.068)	(0.068)	(0.071)
First Generation College=1	0.062	0.052	0.025	-0.438***
	(0.149)	(0.159)	(0.160)	(0.170)
HH Income <80,000=1	-0.069	-0.088	-0.160*	-0.337***
	(0.083)	(0.086)	(0.090)	(0.094)
Hardship			0.458***	0.332**
			(0.147)	(0.151)
Adversity			-0.011	-0.140
			(0.082)	(0.085)
Life Experience			0.007	-0.096
			(0.067)	(0.069)
RAB Points / 100				0.050***
				(0.002)
Graduation class fixed effects	✓	✓	✓	✓
Socioeconomic Measures	✓	✓	✓	✓
WPM components	✓	✓	✓	✓
WPM components $\times$ Class$\geq$2025	✓	✓	✓	✓
Nominations and slate competition measures	✓	✓	✓	✓
Legacy, BGO Interviews, Advanced coursework	✓	✓	✓	✓
Observations	12,300	11,724	11,724	11,724
Pseudo R^2	0.507	0.511	0.512	0.543

Notes: Standard errors below each coefficient in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model 1 uses my preferred sample, Models 2 through 4 use Doctor Gurrea's preferred sample.

district).

That said, my model already accounts for characteristics of congressional districts even in the absence of an underrepresented district variable. Specifically, I include a host of characteristics of congressional slates that are designed precisely to capture these kinds of effects, a fact that Doctor Gurrea failed to mention. For example, we would expect an underrepresented district—which I take to mean one that sends few students to USNA—to have fewer qualified candidates, who in turn have relatively low WPMs. Per Figure 4.1 of my opening report, I control for the number of qualified candidates on the congressional slate, various measures of the WPM on the slate, and how the applicants WPM compares to the top WPMs on the slate.[5] The combined effect of these variables is to capture the relative strength of each congressional slate.

3.2 Doctor Gurrea's suggestions for additional controls are either not in the data or have no impact on the estimates of racial preferences

Doctor Gurrea claims that I "deliberately excluded" (Gurrea 108) certain controls that would reduce my estimate of racial preferences and somehow support his idea that the Black applicants are actually stronger than white applicants on unobserved characteristics. The variables Doctor Gurrea highlight include components of the RAB, as well as measures of hardship and life experiences. Doctor Gurrea fails to mention that I took these variables into account in another way. That is, I *also* showed models with the RAB included and that the coefficient on Black *increased* when I did so.[6] As in other instances, Professor Gurrea could have estimated models with these variables but chose not to do so.

To show the effects of these additional variables, I use Doctor Gurrea's preferred sample and add these controls. But the results are similar using the specifications in either my opening or rebuttal reports. Column (3) of Table 3.1F adds measures for hardship, adversity,

[5] Doctor Gurrea also frames belonging to an underrepresented district in the context of whether the logistic model's independent error assumption holds. However, since my models control for multiple measures of the average quality of nominees on a slate, the fact that the attributes of one nominee affects the outcome of others is well captured by the observables in my model.

[6] Note that they further increased when I removed observations who were missing certain characteristics. See Column (8) of Tables 4.1 and 4.1R in my opening and rebuttal reports.

and life experience to my preferred model. All the race/ethnicity coefficients remain the same. The adversity and life experience coefficients are small and insignificant. The hardship coefficient is positive and significant, but is less than 15% of the Black coefficient. Column (4) of Table 3.1F further adds RAB points. As in my opening and rebuttal reports, adding RAB points yields an even larger Black coefficient, but results in both the coefficients on first generation college and on having a family income of less than $80,000 becoming negative and significant. As I explained in my previous report, including RAB points clouds the interpretation of these coefficients because applicants who are first generation college and have family incomes less than $80,000 are essentially given a preference in the assignment of RAB points which is then effectively taken away in admission.[7]

These results speak directly to Doctor Gurrea's argument that I have no proof racial preferences are larger than socioeconomic preferences (163-167). His argument is that my measures of SES are somehow unreliable. But these measures–coupled with the ones I showed above–are what is available in the USNA data. And these measures matter for *RAB points* but don't matter for *admissions*. Doctor Gurrea doesn't show any other measures, let alone do any analysis showing socioeconomic measures have near the effect of race (if any effect at all). Yet according to Doctor Gurrea we are supposed to believe USNA gives big preferences on the basis of *unmeasured* socioeconomic characteristics. But how could this be when they give so little preference to *measured* socioeconomic characteristics?

3.3 My race/ethnicity categorization matches USNA admissions decisions significantly better than Doctor Gurrea's *for the relevant sample*

Doctor Gurrea argues that my categorization of race/ethnicity is "*ad hoc* and unjustified" (Gurrea, 144) and proposes an alternative classification that he refers to as "data-driven" (Gurrea, 139). Using this new measure, Doctor Gurrea claims to find that my estimates of racial preferences for Black applicants are lower under this new measure, implying that my "regression results are not robust and likely overstated" (Gurrea, 156).

[7]These preferences in the assignment of RAB points are displayed in Tables D.126 and D.126R in my opening and rebuttal reports.

What Doctor Gurrea does is separate race from ethnicity, creating a variable for both. His method is to categorize an applicant who lists multiple races (e.g. Black and Asian American) as multiracial. If an applicant identifies as Black-only (by race) and as Hispanic (by ethnicity), that applicant would be categorized as racially Black and ethnically Hispanic. This is unobjectionable in the abstract. But it is not how college admissions work at *any* of the universities I have studied. And, as I will show, it is a bad choice for modeling USNA's admissions because it yields a less accurate model that does not match well with how USNA actually makes decisions for minority applicants.

One might expect that Doctor Gurrea's supposed *data-driven* method of categorizing race and ethnicity would result in an admissions model that fits the data better than one that he characterizes as "*ad hoc* and unjustified". Yet he himself concedes that his categorization actually fits the data *worse* (Gurrea, Table 8). He tries to downplay the inaccuracy and unreliability of his model by arguing that his and mine are "extremely close" (Gurrea, 158) in terms of model accuracy. But Doctor Gurrea can only claim to be "extremely close" when looking at the entire dataset—obscuring the massive effect that racial preferences have on minority admission. Of course, much of the accuracy of the model is based on non-Hispanic white applicants (the majority group), so it is unsurprising that the fit of the model would change little for the *sample as a whole* with a re-categorization of those who list multiple races/ethnicities.

But how does Doctor Gurrea's categorization do at predicting admissions for those of different race/ethnicity combinations? After all, this is where racial preferences matter. At every university I have studied, racial preferences are largest for Black applicants. Doctor Gurrea finds this with his categorization as well in Exhibit 14. Though both estimates are very large, the coefficient on Black (2.35) is much larger than the coefficient on multiracial (1.39). Note that according to Doctor Gurrea's categorization, this would mean multiracial-Black applicants will get a much smaller bump than single-race Black applicants (and the same bump as non-Black multiracial applicants). In my model, multiracial Black applicants get the same bump as Black applicants.

In Table 3.2F I show how admissions models using my racial/ethnic categorization and Doctor Gurrea's categorization perform in predicting admit rates for different race/ethnicity combinations. I then compare these predictions to the average admit rates for these groups. Column (1) uses my estimation sample; Column (2) uses Doctor Gurrea's estimation sample. Row (1) of Table 3.2F shows that my model, which counts someone as Black regardless of whether they list any other race or ethnicity, does a much better job of predicting the admit rate of multiracial Black applicants. Indeed, Doctor Gurrea's categorization underpredicts the admission rate for this group by *more than 17 percentage points* using my sample, with the magnitude of the underprediction even higher using Doctor Gurrea's estimation sample. Since Doctor Gurrea's categorization substantially underestimates the admissions rates for multiracial Black applicants, we would expect to see it significantly overestimate the admission rate for multiracial applicants who are not Black. And we see this as well in Row (2) Table 3.2F: using Doctor Gurrea's categorization: the predicted admit rate for non-Black multiracial applicants using his categorization is 5 percentage points higher than the actual admit rate for this group.

These same principles apply when considering the effects of Hispanic ethnicity on admissions. According to Doctor Gurrea's categorization, the bump for being Hispanic does not depend on the applicant's race; for my categorization, the Hispanic boost is largest for those whose race is white. Rows (3) and (4) of Table 3.2F show actual and predicted rate for Hispanic applicants whose race is white and non-white respectively. Again, my categorization yields much better predictions than Doctor Gurrea's categorization. Doctor Gurrea's categorization results in a model that underpredicts the average admit rate for white Hispanic applicants by 4 percentage points and overpredicts the admit rate for non-white Hispanic applicants by almost 9 percentage points.

Putting aside the fact that Doctor Gurrea's categorization is inappropriate for USNA's admissions, the effects that Doctor Gurrea finds are still enormous. In his discussion of average marginal effects, what Doctor Gurrea does not show is the baseline admit rates for the different groups. Table 3.3F shows average marginal effects using my categorization and Doctor Gurrea's, both using my estimation sample and his. Even under his categorization, the predicted admit rate for Black applicants is *2.5 times higher* than what it would be if they were treated as white. And even here this is an underestimate of the role of race. The reason is that Doctor Gurrea turns off the race and ethnicity bumps *separately*. The last

Table 3.2F: Actual and Predicted Admit Rates by Race/Ethnicity Combinations

		Predicted Admit Rate	
	Actual	RC1	RC2
Panel A: My Sample			
Multiracial, Black	47.48	43.39	29.95
Multiracial, not Black	43.56	46.28	48.54
Hispanic, white	38.27	36.73	34.27
Hispanic, not white	31.75	35.59	40.53
Panel B: Gurrea's Sample			
Multiracial, Black	48.69	45.38	30.58
Multiracial, not Black	44.74	47.64	49.88
Hispanic, white	40.32	38.40	35.81
Hispanic, not white	32.31	37.28	42.21

RC1 is my race/ethnicity categorization, RC2 is Gurrea's. The predictions are for my preferred model with different race/ethnicity categorizations.

row of Table 3.3F shows that the marginal effects are even higher when both the race and ethnicity bumps are turned off at the same time, which is appropriate when comparing my marginal effects to his.[8]

3.4 Estimating USNA's admissions without race results in substantial underpredictions of actual minority admissions

Doctor Gurrea argues that race/ethnicity is not a predominant factor in admission because a model that does not include this variable (i.e. removes it from the controls) has measures of fit that "fall by less than three percentage points upon removal of race and ethnicity from the model" (Gurrea 170). This is again sleight of hand. The measures of model fit are taken across all applicants. The differences in fit are primarily driven by those who benefit from the racial preferences and the fit for this group is substantially affected by not including

[8]In my categorization, there is only one bump for each race/ethnicity. But in Doctor Gurrea's categorization, an applicant could receive two bumps. Removing both bumps is necessary to make the marginal effects comparable. But even then they are not entirely comparable as our definitions of race are different: my marginal effects are calculated for both single-race and multi-race Black applicants; Doctor Gurrea's marginal effects are calculated for single-race Black applicants.

Table 3.3F: Robustness of Average Marginal Effects of Race/Ethnicity

	My Sample			Gurrea Sample		
Panel A: My Race/Ethnicity Categorization						
	Black	Hispanic	Asian American	Black	Hispanic	Asian American
Admit Rate with Preferences	37.28	35.87	54.78	40.17	37.41	56.34
Admit Rate without Preferences	12.93	24.47	37.64	13.57	25.54	38.38
Average Marginal Effects	24.35	11.40	17.14	26.60	11.88	17.96
Panel B: Gurrea's Race Categorization						
	Black	Asian American	Multiracial	Black	Asian American	Multiracial
Admit Rate with Preferences	31.60	54.79	44.43	35.00	56.62	45.61
Admit Rate without Racial Preferences	12.72	38.34	30.65	13.72	39.33	31.39
Admit Rate without Race and Ethnicity Preferences	11.96	37.81	28.92	12.88	38.80	29.61
Average Marginal Effect of Race	18.88	16.45	13.78	21.28	17.29	14.22
Average Marginal Effect of Race and Ethnicity	19.64	16.98	15.51	22.12	17.82	16.00

In this table I use my preferred model on my sample and Dr. Gurrea's sample, with different racial classifications, and calculate predicted admit probabilities with and without race/ethnicity parameters turned on.

controls for race.

To see the silliness of this argument, suppose USNA's basketball team had characteristics that would lead to certain rejection if they were not a basketball recruit. Clearly being a recruited basketball player would be why these students were admitted. Estimating an admissions model with these students as part of the sample but not allowing for preferences for basketball players will yield a model fit quite similar to one where the model included a control for recruited basketball player. Yet the preferences for basketball players were still determinative for basketball players. Obviously, these preferences for basketball players were not determinative for all other applicants as there are so few basketball players relative to the total applicant pool. But they would be determinative for the few non-basketball players who were rejected because of the admission of basketball players on the basis of their athletic preferences. The same argument holds for racial preferences.

Table 3.4F illustrates the point, displaying model-predicted and actual admit rates for each minority group in a model without any controls for race/ethnicity. Column (1) shows actual admits by race/ethnicity, Column (2) shows the predicted admit rates for my estimation sample without controls for race/ethnicity and Column (3) does the same for Doctor Gurrea's preferred sample. Note that the actual admit rate and the predicted admit difference will be smaller than the marginal effect. The reason for this is that, when race is not controlled for, the other coefficients adjust to try to reconcile why these students are admitted at such a high rate. But even with that, the differences are massive, especially for

Table 3.4F: Actual and Predicted Admit Rates by Race/Ethnicity for a Model without Race/Ethnicity

	My Sample		Gurrea Sample	
	Actual Admit Rate	Predicted Admit Rate	Actual Admit Rate	Predicted Admit Rate
Black	37.28	15.17	40.17	15.42
Hispanic	35.87	28.71	37.41	29.97
Asian American	54.78	46.19	56.34	47.05
Native American/Hawaiian	41.40	35.44	42.91	36.94

Estimates from Arcidiacono preferred model but without controls for race/ethnicity.

Black applicants: absent a direct control for race, an admissions model can account for less than half the number of Black admits. These numbers cannot be rationalized with Doctor Gurrea's claim that "factors other than race and ethnicity provide nearly all the predictive power of the model and are generally causally sufficient, with race and ethnicity being causally necessary at most rarely" (Gurrea 170) *for minority applicants*.

One may then wonder how the results above could possibly be true in light of Doctor Gurrea's claim that race results in "only about 276 extra misclassifications" (Gurrea 170). The implication would seem to be that the other 'non extra' misclassifications were held fixed. But this is not the case as the *composition* of the misclassifications has changed. As the model without race substantially underpredicts the admit rate of Black applicants, it will do a very good of predicting that Black rejects are in fact rejected. So while the model will lose some accuracy from assigning Black admits to be predicted rejects, it will pick up some accuracy from Black rejects who, in the model where race was included, were predicted admits. Extra misclassifications are a useless metric in this context.[9]

3.5 Race is clearly taken into account for Qualified Alternates, contrary to the Latta declaration

Some parts of USNA's admissions procedures - including a substantial portion of admission slots at USNA - are purportedly meant to be very formulaic rather than involving holistic evaluation. For example, in every admission cycle, 150 slots are reserved for admitting students, ranked by their WPM (subject to meeting eligibility criteria) as Qualified Alternates.

[9] Note that Doctor Gurrea makes this same mistake in his discussion of the effects of his alternative racial categorization.

According to Dean Latta,

> After USNA determines the slate of candidates to fill congressional vacancies, it combines all remaining these candidates into a nationwide pool. The 150 highest ranked candidates by WPM are appointed as qualified alternates. In other words, after a candidate has filled a congressional vacancy, remaining qualified nominees from each congressional nominating pool compete against each other in a nationwide pool of congressional alternates. Race and ethnicity are not considered in making selections of candidates as qualified alternates.

In my opening report, I documented a notable distinction between this claim and how Qualified Alternate (QA) admission slots are allocated in practice. The 150 applicants who are initially listed as presumptive QA admits in internal USNA records appear to be selected by virtue of their WPM rank. However, as the admission cycle progresses, many of the individuals initially assigned to these QA slots either (i) decline admission to USNA, or (ii) are reassigned as a winner of a congressional slate.[10] Accordingly, many of the individuals who USNA records as eventually being admitted as a QA have WPMs below the initial threshold. Crucially, I showed that the replacement QA admits are not merely the applicants with the next-highest WPMs among those who have not already won admission via a congressional vacancy. Rather, many of the next highest-WPM candidates are rejected. Among qualified and eligible applicants, white applicants with WPMs just below the initial QA threshold are much less likely to be admitted as QAs than otherwise similar minority students.

Doctor Gurrea claims that my observations are mired in a series of errors and misunderstandings. For example, he dismisses the relevance of any of the cited numbers on the grounds that QA appointments as recorded in the data are merely a product of arbitrary ex-post assignment after the matriculating class is decided (Gurrea 151). He argues that being assigned as a QA admit is not "material to applicants' chances of admission... conditional on an applicant's receiving and accepting an appointment offer, final charging disposition is immaterial to the likelihood of admission." This is rather like arguing that conditional on

[10]Regarding the latter, note that when a prospective congressional slate winner declines USNA admission, a new admit to take that vacancy will generally have to be found.

death, cancer doesn't change mortality. It is also completely inconsistent with Dean Latta's description of the QA admission process quoted above, which stresses that these slots are meant to be assigned based on WPM rank among applicants who did not win admission through their congressional slate. If Doctor Gurrea is correct about what USNA is *actually* doing, Dean Latta's description of QA admissions is incorrect.

To further explore this, I estimate logistic regressions of whether an individual is assigned a QA admission slot. To be consistent with Dean Latta's description of USNA's practices, I take as my sample the set of applicants who are eligible for these slots - qualified applicants with a congressional nomination from a source other than the US Vice-President, who are not listed as congressional slate winners and who did not decline admission.[11] I further condition on being qualified according to the most recent Board result, though my results show substantial racial preferences regardless of this conditioning. I use a broadly similar set of controls from my USNA admission regressions to capture the degree to which QA admission is driven by WPM relative to other factors such as race. Columns (1)-(3) of Table 3.5F show admission for the aforementioned sample of applicants eligible for QA admission, while Columns (4)-(6) focus on the subset with WPMs below their respective year's initial threshold and final threshold; those above the initial threshold are essentially guaranteed admission; those below the final threshold are excluded from QA.[12] In both samples, my estimates show that the effects of race are enormous, especially for Black applicants.

The magnitude of this preference can also be seen by graphing QA admission rates for different WPM increments. In Figure 3.1F, I calculate QA admission rates in my analysis sample by 1000 point WPM bins for Whites and minorities separately, normalizing the final

[11] I also remove a handful of observations with WPMs above the initial QA threshold who appeared to eligible for QA but were charged as Additional Appointees. To be consistent with my logit admissions models, I also exclude blue chip athletes and applicants from the Prep schools. For individuals who decline admission, it is impossible to tell whether they were offered admission as a congressional slate winner, a Qualified Alternate, or through some other channel. It is thus possible that they had won, had lost, or had never been eligible for (by winning a congressional slate) Qualified Alternate admission. I therefore drop people who declined USNA admission from this analysis sample. Since the outcome variable is essentially matriculation as a Qualified Alternate, the estimates capture both differences in admission probabilities and differential yield rates between groups. This is unlikely to be material because it is highly unlikely that racial gaps in accepting admission are substantial relative to the racial preferences in Qualified Alternate assignment I observe.

[12] While there are a small number of exceptions, it is plausible these involve data errors of some form.

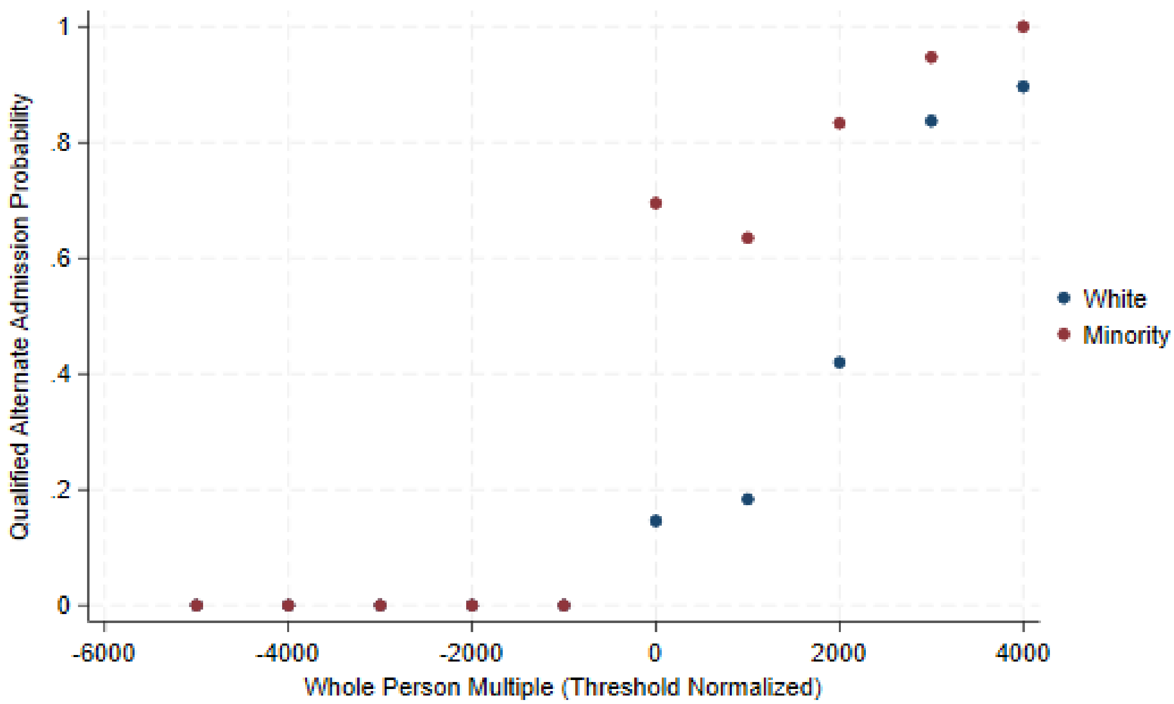
Table 3.5F: Logit Estimates of USNA QA Admissions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Asian	0.925***	3.128***	3.081***	2.397***	3.571***	3.509***
	(0.112)	(0.310)	(0.312)	(0.250)	(0.364)	(0.366)
Black	0.224	3.501***	3.470***	2.766***	4.120***	4.062***
	(0.229)	(0.578)	(0.581)	(0.652)	(0.783)	(0.785)
Declined/Missing	-0.149	-0.781	-0.684	-0.605	-0.929	-0.817
	(0.356)	(0.832)	(0.841)	(0.798)	(0.963)	(0.973)
Hispanic	-0.018	2.199***	2.194***	1.509***	2.444***	2.435***
	(0.154)	(0.402)	(0.404)	(0.340)	(0.443)	(0.444)
Native American / Hawaiian	0.377	2.680***	2.705***	1.403**	2.745***	2.786***
	(0.298)	(0.637)	(0.633)	(0.590)	(0.731)	(0.728)
Female=1	0.545***	0.640***	0.632***	0.416**	0.601**	0.595**
	(0.091)	(0.230)	(0.230)	(0.195)	(0.250)	(0.250)
First Generation College=1		0.077	-0.050		0.101	-0.028
		(0.562)	(0.577)		(0.641)	(0.654)
HH Income <80,000=1		0.107	0.076		0.082	0.040
		(0.300)	(0.302)		(0.332)	(0.334)
Socioeconomic Measures		✓	✓		✓	✓
WPM		✓	✓		✓	✓
Legacy, BGO Interviews, Advanced coursework		✓	✓		✓	✓
RAB Points			✓			✓
Observations	5,091	5,077	5,077	753	751	751
Pseudo R^2	0.036	0.833	0.833	0.183	0.439	0.441

Notes: Standard errors below each coefficient in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model estimated on Classes of 2023–2027. Columns 1-3 include all applicants eligible for QA admission except for excluding Blue Chip Athletes and applicants from the Prep Schools. Columns 4-6 further resrict the sample to individuals whose WPM scores are between their respective year's initial and final QA threshold.

WPM threshold for QA admission in each admission cohort to zero.[13] Naturally, below the final WPM threshold, QA admission rates are zero for all groups. Likewise, in the region close to the highest WPM threshold in each year, admission rates are close to 100%. But in the region between, QA admission rates are dramatically higher for minority applicants than white applicants with similar WPMs.

Figure 3.1F: Qualified Alternate Admission Rates by WPM Bin and Minority Status



Notes: Data are limited to applicants of known race who were eligible for QA (i.e. had a complete application, deemed qualified by the board, qualified both medically and physically, had a congressional nomination, and were not missing WPMs) with WPMs between the initial QA cutoff and 5000 points below the final QA cutoff. A small number of applicants with WPMs above the final QA cutoff who are admitted as Additional Appointees are also removed.

Note that all of these results are consistent with what I showed descriptively in my opening report. Namely, the racial distribution of QA admits is substantially different above the initial QA threshold than below the QA threshold.[14] In Appendix Table A.3, I repeat that analysis here where I am now able to condition on the last Board result for the classes of 2023 and 2024. I was unable to identify this variable in the data as it was under a

[13] Here I exclude people who have unknown or missing race.

[14] See Tables 4.6 and 4.6R in my opening and rebuttal reports.

different name.[15] SFFA asked USNA about whether the most recent Board result existed for the classes of 2023 and 2024 at the 30(b)(6) deposition but did not receive clarity from USNA on this matter.[16] Doctor Gurrea's replication files helped me to make the connection between this variable and the most recent Board result.[17]

[15] The label of the variable was 'Result Meaning'.

[16] 30(b)(6) Deposition Tr. 107: 9-20 (May 28, 2024).

[17] Similarly, I update my analysis of Early Notifies using this information. See Appendix Tables A.4-A.6.

A Appendix Tables

Table A.1: Complete Logit Estimates of USNA Admissions, My Preferred Model vs Dr. Gurrea's Suggestions

	Model 1	Model 2	Model 3	Model 4
Asian	1.449***	1.523***	1.520***	1.297***
	(0.090)	(0.093)	(0.093)	(0.096)
Black	2.958***	3.155***	3.152***	3.307***
	(0.134)	(0.140)	(0.140)	(0.147)
Declined/Missing	0.001	0.000	0.000	-0.002
	(0.222)	(0.232)	(0.232)	(0.238)
Hispanic	1.195***	1.238***	1.238***	1.213***
	(0.091)	(0.094)	(0.095)	(0.098)
Native American / Hawaiian	1.237***	1.261***	1.271***	1.340***
	(0.190)	(0.196)	(0.196)	(0.206)
Female=1	0.329***	0.349***	0.350***	0.198***
	(0.066)	(0.068)	(0.068)	(0.071)
First Generation College=1	0.062	0.052	0.025	-0.438***
	(0.149)	(0.159)	(0.160)	(0.170)
HH Income <80,000=1	-0.069	-0.088	-0.160*	-0.337***
	(0.083)	(0.086)	(0.090)	(0.094)
Missing HH Income=1	-0.080	-0.086	-0.093	-0.158
	(0.100)	(0.103)	(0.103)	(0.107)
Pct of HS attending 4yr College / 100	1.200***	1.280***	1.275***	-0.139
	(0.152)	(0.157)	(0.157)	(0.174)
Private HS	0.301***	0.298***	0.290***	0.146
	(0.102)	(0.104)	(0.104)	(0.108)
Pct FRPL	0.170	0.137	0.115	-0.123
	(0.184)	(0.188)	(0.188)	(0.195)
Avg IRS Zip Code Salary / 100,000	0.032	0.037	0.036	-0.003
	(0.051)	(0.052)	(0.051)	(0.054)
Missing Pct of HS attending 4yr College=1	-0.104	-0.298	-0.302	-0.134
	(0.192)	(0.204)	(0.205)	(0.217)
Missing Private HS status=1	-0.360**	-0.306*	-0.300*	-0.279
	(0.169)	(0.178)	(0.178)	(0.187)
Missing HS Pct FRPL=1	0.055	0.063	0.060	0.019
	(0.099)	(0.100)	(0.100)	(0.104)
Missing Avg IRS Zip Code Salary=1	-0.081	-0.083	-0.088	-0.121
	(0.155)	(0.164)	(0.165)	(0.173)
SAT Math / 100	1.307***	1.311***	1.315***	1.342***
	(0.077)	(0.080)	(0.080)	(0.083)
SAT Verbal / 100	0.827***	0.837***	0.840***	0.978***
	(0.077)	(0.079)	(0.079)	(0.083)

Continued on next page

Table A.1 continued

	Model 1	Model 2	Model 3	Model 4
WPM SRIC / 100	0.571***	0.575***	0.577***	0.671***
	(0.034)	(0.035)	(0.035)	(0.037)
WPM Athletic / 100	0.368***	0.381***	0.382***	0.458***
	(0.026)	(0.026)	(0.026)	(0.028)
WPM Non-Athletic / 100	0.216***	0.221***	0.220***	0.220***
	(0.021)	(0.022)	(0.022)	(0.023)
WPM Combined RSO / 100	0.512***	0.539***	0.543***	0.585***
	(0.026)	(0.027)	(0.027)	(0.028)
CFA / 100	0.407***	0.428***	0.424***	-0.090*
	(0.037)	(0.039)	(0.039)	(0.046)
Missing SAT	4.629***	4.828***	4.884***	5.245***
	(0.483)	(0.496)	(0.498)	(0.511)
1[Class≥2025]=1 × SAT Math / 100	-0.494***	-0.517***	-0.516***	-0.538***
	(0.101)	(0.104)	(0.104)	(0.108)
1[Class≥2025]=1 × SAT Verbal / 100	-0.465***	-0.456***	-0.453***	-0.539***
	(0.108)	(0.112)	(0.112)	(0.117)
1[Class≥2025]=1 × WPM SRIC / 100	0.028	0.072	0.070	0.047
	(0.047)	(0.049)	(0.049)	(0.052)
1[Class≥2025]=1 × WPM Athletic / 100	0.059*	0.073**	0.072**	0.059
	(0.034)	(0.035)	(0.035)	(0.037)
1[Class≥2025]=1 × WPM Non-Athletic / 100	0.152***	0.162***	0.160***	0.193***
	(0.033)	(0.034)	(0.034)	(0.035)
1+ Congressional Noms=1	0.257	0.222	0.207	0.220
	(0.167)	(0.171)	(0.171)	(0.176)
2+ Congressional Noms=1	0.352***	0.371***	0.365***	0.480***
	(0.123)	(0.125)	(0.125)	(0.129)
SECNAV (Regular) Nom=1	0.735***			
	(0.270)			
CDV / Medal of Honor Nom=1	1.064***	1.084***	1.057***	1.253***
	(0.200)	(0.203)	(0.203)	(0.209)
Applying from Nuclear Power School=1	2.916***			
	(0.346)			
Nom on 1+ Type 1 slates	9.486***	9.794***	9.816***	11.652***
	(0.886)	(0.901)	(0.901)	(0.941)
Nom on 1+ Type 2 slates	3.829***	4.482***	4.539***	5.203***
	(0.878)	(0.951)	(0.948)	(0.898)
Nom on Principal slate (not principal)	-0.225*	-0.216*	-0.215	-0.173
	(0.130)	(0.131)	(0.131)	(0.134)
Principal on 1+ slates	4.421***	4.536***	4.545***	4.897***
	(0.137)	(0.141)	(0.141)	(0.150)
Within 4000 WPM points on Type 1 slate	0.118	0.105	0.107	-0.021
	(0.082)	(0.083)	(0.083)	(0.085)

Continued on next page

Table A.1 continued

	Model 1	Model 2	Model 3	Model 4
Within 4000 WPM points on Type 2 slate	0.509***	0.489***	0.485***	0.232
	(0.167)	(0.169)	(0.170)	(0.173)
Max WPM on slate & 4000+ above all others	1.364***	1.311***	1.311***	0.761***
	(0.200)	(0.202)	(0.201)	(0.210)
log (no. Type 1 competitors + 1)	-0.666***	-0.702***	-0.703***	-0.904***
	(0.101)	(0.103)	(0.103)	(0.107)
log (no. Type 2 competitors + 1)	-1.342***	-1.397***	-1.402***	-1.598***
	(0.141)	(0.143)	(0.143)	(0.149)
min of Avg (WPM / 10,000) on Type 1 slates	-1.182***	-1.216***	-1.218***	-1.418***
	(0.127)	(0.129)	(0.129)	(0.134)
min of Avg (WPM / 10,000) on Type 2 slates	-0.067	-0.141	-0.147	-0.158
	(0.136)	(0.146)	(0.146)	(0.139)
TotalNominations=2	0.015	-0.003	-0.001	-0.087
	(0.091)	(0.094)	(0.094)	(0.097)
TotalNominations=3	0.309**	0.306*	0.313**	0.166
	(0.154)	(0.157)	(0.157)	(0.163)
TotalNominations=4	0.666**	0.675**	0.700**	0.200
	(0.314)	(0.319)	(0.319)	(0.333)
TotalNominations=5	2.550**	2.603**	2.631**	2.407
	(1.290)	(1.323)	(1.323)	(1.613)
Graduating Class=2024	0.368***	0.336***	0.337***	0.340***
	(0.087)	(0.088)	(0.088)	(0.092)
Graduating Class=2025	6.443***	6.083***	6.077***	6.809***
	(0.829)	(0.870)	(0.871)	(0.907)
Graduating Class=2026	6.729***	6.396***	6.396***	7.269***
	(0.825)	(0.867)	(0.867)	(0.904)
Graduating Class=2027	6.226***	5.906***	5.907***	6.611***
	(0.827)	(0.868)	(0.868)	(0.905)
Legacy (USNA)=1	0.508***	0.501***	0.503***	0.338**
	(0.133)	(0.135)	(0.136)	(0.141)
Legacy (non-USNA Svc Academy)=1	-0.342**	-0.369**	-0.371**	-0.487***
	(0.155)	(0.157)	(0.157)	(0.165)
Any RAB for AP, IB, or Honors courses=1	0.179***	0.177***	0.179***	-0.022
	(0.059)	(0.061)	(0.061)	(0.064)
BGO Top 25 pct	-0.397***	-0.392***	-0.389***	-0.150**
	(0.070)	(0.071)	(0.071)	(0.075)
BGO Above Average	-0.614***	-0.612***	-0.608***	-0.294***
	(0.101)	(0.102)	(0.103)	(0.107)
BGO Average	-0.838***	-0.834***	-0.829***	-0.542***
	(0.145)	(0.147)	(0.147)	(0.154)
BGO Below Average	-1.858***	-1.872***	-1.914***	-1.762***
	(0.420)	(0.425)	(0.425)	(0.459)

Continued on next page

Table A.1 continued

	Model 1	Model 2	Model 3	Model 4
BGO Not Rec / Withdrawn	-0.865**	-0.889**	-0.907**	-0.792*
	(0.384)	(0.388)	(0.391)	(0.426)
BGO Not Observed	-2.371***	-0.948	-0.900	-0.477
	(0.641)	(0.797)	(0.797)	(0.829)
Hardship			0.458***	0.332**
			(0.147)	(0.151)
Adversity			-0.011	-0.140
			(0.082)	(0.085)
Life Experience			0.007	-0.096
			(0.067)	(0.069)
RAB Points / 100				0.050***
				(0.002)
Constant	-28.826***	-29.337***	-29.384***	-30.060***
	(0.809)	(0.842)	(0.844)	(0.890)
Observations	12,300	11,724	11,724	11,724
Pseudo R^2	0.507	0.511	0.512	0.543

Notes: Standard errors below each coefficient in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model 1 uses my preferred sample, Models 2 through 4 use Doctor Gurrea's preferred sample.

Table A.2: Complete Logit Estimates of USNA Qualified Alternate Admissions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Asian	0.925***	3.128***	3.081***	2.397***	3.571***	3.509***
	(0.112)	(0.310)	(0.312)	(0.250)	(0.364)	(0.366)
Black	0.224	3.501***	3.470***	2.766***	4.120***	4.062***
	(0.229)	(0.578)	(0.581)	(0.652)	(0.783)	(0.785)
Declined/Missing	-0.149	-0.781	-0.684	-0.605	-0.929	-0.817
	(0.356)	(0.832)	(0.841)	(0.798)	(0.963)	(0.973)
Hispanic	-0.018	2.199***	2.194***	1.509***	2.444***	2.435***
	(0.154)	(0.402)	(0.404)	(0.340)	(0.443)	(0.444)
Native American / Hawaiian	0.377	2.680***	2.705***	1.403**	2.745***	2.786***
	(0.298)	(0.637)	(0.633)	(0.590)	(0.731)	(0.728)
Female=1	0.545***	0.640***	0.632***	0.416**	0.601**	0.595**
	(0.091)	(0.230)	(0.230)	(0.195)	(0.250)	(0.250)
Graduating Class=2024	0.108	1.455***	1.468***	-0.119	1.243***	1.268***
	(0.134)	(0.337)	(0.338)	(0.260)	(0.355)	(0.357)
Graduating Class=2025	0.619***	2.049***	2.036***	0.300	1.952***	1.949***
	(0.133)	(0.367)	(0.368)	(0.307)	(0.415)	(0.416)
Graduating Class=2026	0.552***	3.405***	3.441***	1.038***	3.514***	3.556***
	(0.134)	(0.401)	(0.402)	(0.309)	(0.464)	(0.466)
Graduating Class=2027	0.237*	1.964***	1.955***	-0.261	1.525***	1.527***
	(0.134)	(0.343)	(0.344)	(0.268)	(0.371)	(0.372)
First Generation College=1		0.077	-0.050		0.101	-0.028
		(0.562)	(0.577)		(0.641)	(0.654)
HH Income <80,000=1		0.107	0.076		0.082	0.040
		(0.300)	(0.302)		(0.332)	(0.334)
Missing HH Income=1		0.185	0.181		0.007	-0.004
		(0.348)	(0.348)		(0.373)	(0.373)
Pct of HS attending 4yr College		0.001	-0.001		0.001	-0.001
		(0.005)	(0.006)		(0.006)	(0.006)

Continued on next page

Table A.2 continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Private HS × 100		0.000	0.000		0.001	0.001
		(0.004)	(0.004)		(0.004)	(0.004)
Pct FRPL		-0.004	-0.004		-0.003	-0.003
		(0.007)	(0.007)		(0.008)	(0.008)
Avg IRS Zip Code Salary / 10,000		0.003*	0.003		0.003	0.003
		(0.002)	(0.002)		(0.002)	(0.002)
Missing Pct of HS attending 4yr College=1		-0.079	-0.144		0.290	0.258
		(0.952)	(0.963)		(1.111)	(1.121)
Missing Private HS status=1		-0.102	-0.079		0.014	0.050
		(0.712)	(0.711)		(0.725)	(0.723)
Missing HS Pct FRPL=1		0.138	0.127		0.129	0.110
		(0.351)	(0.352)		(0.363)	(0.364)
Missing Avg IRS Zip Code Salary=1		-0.074	-0.109		-0.100	-0.149
		(0.659)	(0.657)		(0.681)	(0.679)
WPM Above Initial QA Cutoff		1.001	0.991			
		(0.658)	(0.658)			
WPM Score		0.174***	0.173***		0.145***	0.144***
		(0.011)	(0.011)		(0.013)	(0.013)
CFA / 100		-0.169	-0.255		-0.193	-0.287*
		(0.143)	(0.160)		(0.151)	(0.171)
Legacy (USNA)=1		0.671	0.655		0.883*	0.858*
		(0.429)	(0.428)		(0.467)	(0.469)
Legacy (non-USNA Svc Academy)=1		-0.484	-0.496		-0.561	-0.585
		(0.584)	(0.585)		(0.617)	(0.620)
Any RAB for AP, IB, or Honors courses=1		0.157	0.155		0.087	0.088
		(0.228)	(0.228)		(0.247)	(0.247)
BGO Top 25 pct		-0.146	-0.103		-0.381	-0.337
		(0.245)	(0.248)		(0.259)	(0.263)
BGO Above Average		-0.281	-0.227		-0.719	-0.648

Continued on next page

Table A.2 continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
		(0.414)	(0.418)		(0.461)	(0.465)
BGO Average		-0.303	-0.307		-0.708	-0.727
		(0.581)	(0.579)		(0.628)	(0.627)
BGO Below Average		-0.663	-0.547		-1.206	-1.064
		(1.624)	(1.632)		(2.113)	(2.131)
BGO Not Rec / Withdrawn		-4.746	-4.712			
		(3.758)	(3.756)			
BGO Not Observed		-3.873	-3.756			
		(5.943)	(5.986)			
RAB Points / 100			0.009			0.010
			(0.007)			(0.008)
Constant	-2.492***	-129.553***	-128.857***	-1.464***	-107.664***	-106.990***
	(0.101)	(7.832)	(7.845)	(0.212)	(9.226)	(9.255)
Observations	5,091	5,077	5,077	753	751	751
Pseudo R^2	0.036	0.833	0.833	0.183	0.439	0.441

Notes: Standard errors below each coefficient in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model estimated on Classes of 2023–2027. Columns 1-3 include all applicants eligible for QA admission except for excluding Blue Chip Athletes and applicants from the Prep Schools. Columns 4-6 further resrict the sample to individuals whose WPM scores are between their respective year's initial and final QA threshold.

Table A.3: Shares of Candidates Above and Below Inital QA Cutoffs and QA Rate Below Initial Cutoff by Race

Race	Share Above Initial Threshold	Share Below Initial Threshold	Share of QA Admits Above Initial Threshold	Share of QA Admits Below Initial Threshold	QA Rate Below Threshold
White	72.01	74.13	72.05	54.93	29.73
Black	2.39	2.63	2.41	5.67	86.36
Hispanic	8.37	5.99	8.19	9.55	64.00
Asian	13.88	13.89	13.98	26.57	76.72
Native American / Hawaiian	1.67	1.68	1.69	2.39	57.14
Declined / Missing	1.67	1.68	1.69	0.90	21.43
Total	418	835	415	335	40.12

Notes: Sample restricted to applicants who were eligible to be a Qualified Alternate, had a Most Recent Board Result of Early Notify, Qualified, or Qualified Prep Pool, and who were not admitted through another channel. The row labeled Total lists the total observation counts and the averge rate of being admitted as a Qualified Alternate while having a WPM score below the intital threshold. Applicants must be above the final QA threshold to be included in the sample.

Table A.4: Admit Rate and Application Share by Most Recent Board Result

Board Result	Admit Rate	Share of Applicants	Share of Admits
Panel A: Full Sample			
Early notify	77.75	37.75	85.55
Qualified	14.74	31.47	13.53
Qualified, Prep Pool	9.75	3.00	0.85
Not Qualified	0.00	18.09	0.00
Not Qualified, Prep Pool	0.15	9.67	0.04
USNA Deferred	50.00	0.02	0.03
Total	34.31	20,150	6,913
Panel B: Gurrea Sample			
Early notify	82.08	45.32	82.72
Qualified	22.71	32.02	16.17
Qualified, Prep Pool	14.08	3.26	1.02
Not Qualified	0.00	10.03	0.00
Not Qualified, Prep Pool	0.25	9.35	0.05
USNA Deferred	100.00	0.02	0.03
Total	44.97	12,856	5,781

Full sample restricted to domestic, complete applications that have a Most Recent Board Result. The row labeled "Total" lists the average admit rate of the sample, as well as the total observation count.

Table A.5: Qualified Any Share, Early Notify Share of Qualified Any, and Average WPM Scores by Race

Race	Share Qualified Any	Early Notify/ Qualified Any	WPM	WPM Not Qualified	WPM Qualified	WPM Early Notify
Panel A: Full Sample						
White	76.28	47.00	67,640	60,541	67,886	70,822
Hispanic	60.34	55.62	66,117	60,258	67,085	68,759
Asian	77.88	65.30	68,600	61,467	68,672	70,633
Black	54.06	80.95	63,390	58,439	63,915	63,932
Native American / Hawaiian	62.58	62.70	66,433	59,641	66,984	68,558
Declined / Missing	73.84	41.34	67,938	61,192	67,481	71,599
Panel B: Full Sample without Blue Chip Athletes and Prep Pool						
White	74.07	40.00	67,859	60,557	68,374	73,006
Hispanic	55.20	44.82	66,214	60,238	67,851	71,377
Asian	75.79	60.74	68,852	61,436	69,198	71,922
Black	36.96	61.03	63,441	58,449	66,792	68,642
Native American / Hawaiian	57.71	53.04	66,585	59,585	68,262	71,735
Declined / Missing	73.15	37.13	67,912	61,235	67,652	72,856
Panel C: Gurrea Sample without Blue Chip Athletes and Prep Pool						
White	82.68	46.71	67,859	61,385	69,216	73,452
Hispanic	66.13	52.58	66,214	61,273	68,745	71,845
Asian	84.64	67.89	68,852	62,707	69,966	72,252
Black	51.52	64.43	63,441	59,523	67,128	68,821
Native American / Hawaiian	70.30	58.82	66,585	61,111	68,898	72,229
Declined / Missing	83.17	42.77	67,912	62,812	68,944	73,865

Full sample restricted to eligible domestic, complete applications that had a Most Recent Board Result (excluding "USNA Deferred") and a WPM Score. "Qualified Any" refers to applicants with a Most Recent Board Result of "Early Notify", "Qualified", or "Qualified, Prep Pool".

Table A.6: Complete Logit Estimates of Early Notify Board Result

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Asian	0.629***	0.778***	1.107***	1.473***	1.307***	1.518***
	(0.047)	(0.061)	(0.075)	(0.098)	(0.084)	(0.100)
Black	-0.495***	-0.122	1.953***	2.761***	2.356***	2.781***
	(0.070)	(0.086)	(0.115)	(0.150)	(0.131)	(0.153)
Declined/Missing	0.030	-0.081	0.036	-0.090	-0.062	-0.111
	(0.125)	(0.150)	(0.185)	(0.234)	(0.204)	(0.237)
Hispanic	-0.176***	-0.071	0.805***	1.038***	0.835***	1.043***
	(0.051)	(0.062)	(0.079)	(0.101)	(0.086)	(0.102)
Native American / Hawaiian	0.174*	0.205	1.011***	1.177***	1.033***	1.160***
	(0.104)	(0.129)	(0.168)	(0.212)	(0.184)	(0.215)
Female=1	0.361***	0.372***	0.551***	0.658***	0.568***	0.639***
	(0.035)	(0.043)	(0.056)	(0.071)	(0.062)	(0.072)
First Generation College=1	-0.574***	-0.604***	0.196	0.015	0.126	0.084
	(0.090)	(0.112)	(0.134)	(0.174)	(0.146)	(0.176)
HH Income <80,000=1	-0.381***	-0.260***	0.254***	0.182**	0.215***	0.191**
	(0.045)	(0.057)	(0.070)	(0.090)	(0.078)	(0.091)
Missing HH Income=1	-0.630***	-0.244***	-0.157*	-0.196*	-0.145	-0.221**
	(0.053)	(0.069)	(0.084)	(0.108)	(0.094)	(0.110)
Pct of HS attending 4yr College / 100	0.833***	0.742***	1.554***	1.954***	1.883***	2.067***
	(0.082)	(0.100)	(0.131)	(0.166)	(0.144)	(0.168)
Private HS	-0.075	-0.075	0.311***	0.311***	0.237***	0.330***
	(0.053)	(0.069)	(0.084)	(0.110)	(0.092)	(0.111)
Pct FRPL	0.105	0.074	0.122	0.049	0.097	0.087
	(0.095)	(0.123)	(0.147)	(0.192)	(0.161)	(0.194)
Avg IRS Zip Code Salary / 100,000	-0.029	0.017	-0.117***	-0.052	-0.062	-0.030
	(0.026)	(0.035)	(0.040)	(0.054)	(0.043)	(0.055)
Missing Pct of HS attending 4yr College=1	-0.238**	-0.513***	-0.167	-0.356*	-0.038	-0.351*
	(0.117)	(0.136)	(0.169)	(0.203)	(0.191)	(0.206)

Continued on next page

Table A.6 continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Missing Private HS status=1	-0.315***	-0.115	-0.162	-0.158	-0.343**	-0.199
	(0.107)	(0.116)	(0.158)	(0.180)	(0.170)	(0.183)
Missing HS Pct FRPL=1	0.493***	-0.036	0.258***	-0.021	0.172*	-0.011
	(0.061)	(0.067)	(0.092)	(0.105)	(0.100)	(0.107)
Missing Avg IRS Zip Code Salary=1	-0.150	-0.309***	0.006	-0.009	0.181	0.056
	(0.100)	(0.109)	(0.145)	(0.168)	(0.156)	(0.170)
Graduating Class=2024	0.008	0.023	-0.002	-0.016	-0.084	-0.044
	(0.046)	(0.057)	(0.071)	(0.091)	(0.079)	(0.092)
Graduating Class=2025	0.140***	0.365***	0.362***	0.407***	0.272***	0.361***
	(0.049)	(0.063)	(0.082)	(0.107)	(0.091)	(0.109)
Graduating Class=2026	0.274***	0.215***	0.602***	0.535***	0.470***	0.494***
	(0.052)	(0.063)	(0.083)	(0.104)	(0.091)	(0.106)
Graduating Class=2027	0.220***	0.154**	0.772***	0.742***	0.726***	0.719***
	(0.049)	(0.060)	(0.081)	(0.101)	(0.089)	(0.103)
SAT Math / 100			1.361***	1.460***	1.373***	1.467***
			(0.047)	(0.060)	(0.052)	(0.061)
SAT Verbal / 100			0.706***	0.806***	0.713***	0.793***
			(0.047)	(0.061)	(0.052)	(0.062)
WPM SRIC / 100			0.806***	0.906***	0.845***	0.913***
			(0.023)	(0.030)	(0.026)	(0.031)
WPM Athletic / 100			0.493***	0.559***	0.523***	0.564***
			(0.016)	(0.021)	(0.018)	(0.022)
WPM Non-Athletic / 100			0.374***	0.417***	0.394***	0.423***
			(0.015)	(0.019)	(0.016)	(0.019)
WPM Combined RSO / 100			0.747***	0.865***	0.817***	0.894***
			(0.023)	(0.030)	(0.026)	(0.031)
CFA / 100			0.770***	0.796***	0.804***	0.819***
			(0.032)	(0.042)	(0.035)	(0.042)
Missing SAT			8.470***	9.850***	8.945***	9.874***

Continued on next page

Table A.6 continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
			(0.354)	(0.490)	(0.405)	(0.498)
Legacy (USNA)=1					0.278**	0.289**
					(0.123)	(0.142)
Legacy (non-USNA Svc Academy)=1					0.111	-0.022
					(0.147)	(0.165)
Any RAB for AP, IB, or Honors courses=1					0.435***	0.393***
					(0.055)	(0.064)
1+ Congressional Noms=1					0.180*	0.093
					(0.104)	(0.123)
2+ Congressional Noms=1					0.171***	0.197***
					(0.065)	(0.074)
SECNAV (Regular) Nom=1					1.149***	
					(0.274)	
CDV / Medal of Honor Nom=1					2.202***	2.179***
					(0.186)	(0.213)
Applying from Nuclear Power School=1					3.061***	
					(0.357)	
Constant	-1.653***	-1.063***	-33.067***	-36.480***	-34.870***	-37.307***
	(0.076)	(0.094)	(0.543)	(0.748)	(0.633)	(0.776)
Observations	21,935	11,701	20,055	11,698	16,261	11,698
Pseudo R^2	0.039	0.035	0.534	0.557	0.549	0.567

Notes: Standard errors below each coefficient in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model estimated on Classes of 2023–2027. Columns 1, 3 and 5 includes all domestic applicants with a Most Recent Board Result except for Blue Chip Athletes and those applying from Prep Pool. Columns 2, 4 and 6 further resrict the sample to individuals who completed the USNA application and are eligible for admission.