Is Affirmative Action Responsible For The Achievement Gap Between Black And White Law Students?": A Correction, A Lesson, and An Update

By Katherine Y. Barnes[1]

Abstract

Introduction

In 2007, the Northwestern University Law Review published an essay that I wrote entitled *Is Affirmative Action Responsible for the Achievement Gap Between Black and White Law Students?*[2] The essay joined a scholarly debate regarding the potential deleterious effects of affirmative action in the law school admissions process. The debate was ignited by an empirical study published in the Stanford Law Review by Professor Richard Sander[3] in 2004 that suggested that affirmative action policies were counterproductive, followed by a series of replies from other academics, along with rejoinders from Professor Sander.[4]

The purpose of my essay was to provide a framework with which to test different theories regarding the effects of affirmative action. The essence of Professor Sander's claim is that minority students matriculate to law schools that are above their capabilities because of affirmative action, and that this "mismatch" causes them to disengage with the learning process and learn less than they otherwise would at a lower-ranked institution.

While recognizing that the mismatch hypothesis questions whether students and their institutions maximize the student's success in law school and in law life, I argued that the insight behind the mismatch hypothesis is unrelated to race - as a theoretical matter mismatch relies solely on the interaction of student ability and institutional quality as a trigger. I framed a more accurate test of the mismatch hypothesis, which

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2 Katherine Y. Barnes, *Is Affirmative Action Responsible for the Achievement Gap Between Black and White Law Students?*, 101 Northwestern L. Rev 59 (2007).

3 Richard H. Sander, *A Systematic Analysis of Affirmative Action in American Law Schools*, 57 STANFORD L. REV. 367 (2004)

4 Many of the replies to Professor Sander questioned his methods and results. See, e.g., Ian Ayres and Richard Brooks, *Does Affirmative Action Reduce the Number of Black Lawyers?,* 57 STAN. L. REV. 1807 (2005); David L. Chambers, Timothy T. Clydesdale, William C. Kidder, and Richard O. Lempert, *The Real Impact of Eliminating Affirmative Action in American Law Schools: An Empirical Critique of Richard Sander's Study*, 57 STANFORD L. REV. 1855 (2005); Michele Landis Dauber, *The Big Muddy*, 57 STAN. L. REV. 1899 (2005); Daniel E. Ho, *Scholarship Comment: Why Affirmative Action Does Not Cause Black Student to Fail the Bar*, 114 YALE L.J. 1997 (2005); Daniel E. Ho, *Affirmative Action's Affirmative Actions: A Reply to Sander*, 114 YALE L.J. 2011 (2005); Jesse Rothstein and Albert Yoon, *Mismatch in Law School*, Northwestern Law & Econ Research Paper No. 881110, *available at* http://www.princeton.edu/~jrothst/research.html (May 2009). Others questioned the conclusions that should be drawn from his results. See David B. Wilkins, *A Systematic Response to Systematic Disadvantage: A Response to Sander*, 57 STAN. L. REV. 1915 (2005). Professor Sander replied to several critics directly. Richard Sander, *A Reply to Critics*, 57 STAN. L. REV. 1963 (2005); Richard Sander, *Mismeasuring the Mismatch*, 114 YALE L.J. 2005 (2005). There are also several other articles that are not empirical in nature.

controlled for other aspects of individual law school culture and how they might interact with student race to create different experiences of law school, which, in turn, could affect student outcomes.

In 2008, Professors Doug Williams and Richard Sander contacted me regarding replication of my results. Unfortunately, I had changed institutions between the time the article was slated for publication and this contact. Due to my own negligence, while I thought I had transferred all of my files to my computer at my new institution, I had not. Thus, I did not have the original programs that I used to analyze the data. I reconstructed the programs for Professors Williams and Sander and their colleague Dr. Roger Bolus but was not able to replicate exactly the same results as in the original. Like all good researchers my first commitment is to the truth, or as much thereof as the limits of logic, method, data and human capacities allow. This correction followed.

Research is a process of formulating and reformulating theories on the basis of new information. Empirical research, in particular, involves the often public debate regarding the appropriate methods, analysis, and conclusions to be drawn from data. By its nature all empirical research is imperfect in some way. Some imperfections are correctible, and while all empirical researchers hope that mistakes in analysis are infrequent, the academic process of replication, further investigation and debate (like the methods of science more generally) is built to find flaws in current research in order to improve knowledge.

I am very grateful to Professor Williams, Professor Sander and Dr. Bolus for their effort in replicating my results, their diligence in helping to advance our understanding of the empirical validity of the mismatch hypothesis, and I mix a sense of embarrassment at the problems with my original analysis with the pleasure of seeing the methods of science and scholarly discourse work the way they should.

Before revisiting the main arguments and results of my 2007 essay, let me take a moment to reflect on the process by which law professors, in particular, publish their research, and how my error could be avoided in the future. Of course, the most obvious way to avoid published errors is to not make errors in the first place. This is always preferable, but not always practical.

For myself, my personal practice for submitted papers has changed. The best practice to avoid mistakes in coding is to double code every program,[5] and I now do so. I also keep a pristine copy of the program used for the results in the submitted version of the paper in a separate "read-only" directory, where future changes in the program will not be confused with the analysis from the submitted paper.

Beyond the personal responsibility of researchers, law reviews also have the responsibility to facilitate replication.[6] Journals should have a systematic policy that requires the programs that support results to be submitted with the article,[7] the posting of programs and datasets on law journal websites, and the publishing of technical appendices which explain more of the details of the analysis (again, on the law review website). Because of the large number of law reviews, and the fact that their editorships change every year, long-term policies are more difficult to implement and retain. While difficult, law reviews should commit to these best

[5] Optimally, double-coding requires two different people independently coding the same general algorithm using two different statistical packages, making sure that the output matches. This is time-consuming and expensive safeguard, but catches most errors before they are published. This tests whether the logic of the algorithm is implemented correctly and helps find errors in the logic itself.

[6] I use the word "replication" in a narrower sense than is generally meant in social science research: replication generally describes replicating an entire experiment, and obtaining similar results. See Dauber, supra n. 4 at [PINCITE]. In this case, I use replication more narrowly to mean simply repeating the analysis with the same dataset.

[7] Transparency is the best way to curtail errors. For example, Professor Sander makes all of his programs and data available on his website as I have for this correction. See XXX. While I commend this practice as it facilitates replication, law reviews should not leave the decision whether to make this information available to the individual researcher. Transparency also suggests that all modeling decisions be explicit. Unfortunately, in the context of a law review article written for a non-technical audience, including every specific decision is unrealistic, although technical appendices, published on the law review's website, are helpful in this regard.

practices when evaluating and publishing empirical research; indeed, it is optimal to have a more comprehensive clearinghouse, such as SSRN, which would alleviate these structural pressures by providing one well maintained location to house programs and datasets. While I provide some policies that law reviews could implement, I take full responsibility for my error in not maintaining my program appropriately, as well as any errors in analysis which that program would have illuminated. Nonetheless, I am pleased that Northwestern Law Review has agreed to make available a copy of all my data and programs on their web site to aid future research and policy on this topic.[8]

The Original 2007 Essay

My 2007 essay engaged in the debate over the effects of affirmative action on law student outcomes in four primary ways. First, the essay clarified the argument over what mismatch is – specifically, that the mismatch theory is unrelated to the race of the students who are at risk for being outmatched by their classmates Second, it explicitly separated two theories that may explain black law students' relatively poorer law school grades and tested these theories separately: mismatch, triggered by affirmative action programs that put black students at higher risk of being outmatched, and what I termed "race-based barriers," which is a broad category meant to encapsulate the individual law school culture and how it might create or perpetuate barriers to success that are based upon racial categories.[9] Third, the essay reported the results of alternative policy simulations to determine the effect of affirmative action on the number of new black lawyers each year, the number of black graduates, and the number of black law students who obtain well paying jobs after graduation, with the goal of testing whether different policies produce significantly different numbers, as Professor Sander argued in his 2004 article. Fourth, the essay reinforced the significant limitations of the data, including several coding issues and, more generally, significant selection bias problems, and provided an experimental design that would alleviate these data problems. In addition, the modeling structure I used to test the two theories and simulate alternative policies allowed for a more flexible relationship between student credentials (specifically LSAT and undergraduate GPA) and student outcomes after law school.

There are three primary limitations to the data in these studies. As I articulated in the original essay, they are "(1) no knowledge of the specific school each student attended; (2) incomplete measurement of student credentials, relying solely on LSAT and UGPA scores; and, to a lesser extent, (3) bar passage results that are not state-specific." [10] Incomplete measurement of student credentials, is the most troubling, because it creates selection bias: those students who matriculate to high-ranking schools with low measured credentials likely have unusually high *unmeasured* credentials, and vice-versa. Selection bias can bias statistical analyses significantly, making inference less certain. The data provide only indicate which of six broad groups of schools to which a student matriculated; I consolidate these into 4 school types, which are roughly similar to tiers.[11]

The 2007 results generally found relatively strong evidence of the opposite of a-mismatch effect (an anti-mismatch effect), and some evidence of cultural differences across schools that affect minority students differently, which I termed a race-based barriers effect. These results have changed substantially.[12]

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8 CITE to NW law review site; see also KYB website.

9 While I use the term "race-based barriers", I cannot make the causal claim that these barriers are caused by race; instead, my model measures the association of race, school types and their interaction with student outcomes.

10 Barnes, supra n. 2 at [PINCITE].

11 The four school types are Historically Black Schools, Low range schools, Midrange schools, and Top 30 schools.

12 In their response, Sander et al. make slightly different coding decisions, which result in slightly different results. Based upon our exchange of programs, I believe this different is due to the fact that I drop those individuals who are "out of study" from the analysis, while Sander et al. assume negative outcomes for these individuals. "Out of study" means that the student was not a part of the follow-up,

Revised Results

Tables 1A, 2A, and 3A provide the results of the logistic regression models that are relevant to the mismatch test while Tables 1B-3B provide the results of the models that are relevant to the race-based barriers test.[13] For convenience, the tables also provide the original results from the 2007 article.

As detailed in the original essay, mismatch requires a specific pattern of outcomes across school types. Specifically, the probability of a positive outcome – graduating from the law school, for example – should be higher for lower ranked schools. Mismatch might only occur for the students with very low credentials, but there is little theoretical basis to conclude that mismatch would happen in some schools by not others .Because Tables 1A reports the difference in probability of graduating from the same law school to which one initially matriculated between the listed school type and midrange schools, the pattern consistent with mismatch is a monotone, but not necessarily linear, negative progression in graduation rates as school quality increases. In addition, because the results here – and in the original essay – did not control for selection bias, "I am cautious about drawing conclusions from the results due to significant data limitations"[14] Thus, one requires clear evidence of mismatch – or anti-mismatch – to make tentative conclusions in either direction. The results here do not meet this standard.

Table 1A provides 4 panels of comparisons, based on different student credentials. None of the panels demonstrate this mismatch pattern. Historically Black Schools (HBS) have higher graduation rates than midrange schools. At the lower credentials levels, where mismatch is more likely, low range schools have lower graduation rates than midrange schools. The reported results from the 2007 article demonstrated an anti-mismatch effect, and so the results are significantly different. The corrected results do not, however, support the mismatch hypothesis.

Table 1A: Logistic Regression of Graduation Rate Allowing for Mismatch and Race-Based Barriers
Results Relevant to Mismatch Testing

Variable	ΔPr(Graduate) [15]	
	2007 Article	Revised Results
Mismatch (compare to Midrange Schools) (Fixed student credentials at 5th percentile)[16]		
Comparison (Baseline) Probability	83.3%	85.4%

generally because they did not graduate from the same school to which they originally matriculated. CITE.

[13] All report results are from logistic regression models which predict the probability of a positive outcome (graduation, bar passage, or obtaining a well-paying job) given a flexible function form for student credentials (allowing up to cubic powers of LSAT, UGPA, and their interactions – 9 variables), race (white, Black, Asian, Other), school type, school type * race interactions (9 variables), and school type * credentials interactions (27 variables).

[14] Barnes, supra n. 2 at 1759.

[15] This number provides the change in probability between the given characteristic and the control, holding credentials at the specified value and race at its modal value, white.

[16] In the 2007 essay, I defined the 5th percentile of student credentials as the combination of the 5th percentile of LSAT and the 5th percentile of UGPA. This, however, is far below the 5th percentile of overall student credentials, because most students who have the 5th percentile of LSAT do better on UGPA, and vice-versa. Indeed, less than three-quarters of one percent of students have credentials at or below both 5th percentile levels. For these results, I defined the percentile levels based upon a weighted average of LSAT and UGPA, as Prof. Sander did in his original article. See Sander, supra n. 2 at [PINCITE]

Historically Black Schools	-4.1%	5.9%
Low range Schools	-11.3%	-4.7%
Midrange Schools	--	--
Top 30 Schools	5.3%	0.8%
Mismatch (compare to Midrange Schools) (Fixed student credentials at 10th percentile)		
Comparison (Baseline) Probability	87.2%	86.4%
Historically Black Schools	-4.8%	5.4%
Low range Schools	-9.8%	-3.6%
Midrange Schools	--	--
Top 30 Schools	4.4%	0.7%
Mismatch (compare to Midrange Schools) (Fixed student credentials at 25th percentile)		
Comparison (Baseline) Probability	89.7%	90.7%
Historically Black Schools	-1.8%	2.1%
Low range Schools	-4.9%	0.2%
Midrange Schools	--	--
Top 30 Schools	4.6%	2.2%
Mismatch (compare to Midrange Schools) (Fixed student credentials at 50th percentile)		
Comparison (Baseline) Probability	91.7%	91.6%
Historically Black Schools	-0.1%	1.6%
Low range Schools	-0.8%	1.8%
Midrange Schools	--	--
Top 30 Schools	4.3%	3.1%
Overall School Type * Credentials Interactions (27 variables)[17]: p-value = 0.0225		

Table 1B focuses on the race-based barriers portion of the model, still with respect to graduation rates. The results here are not substantially different in the corrected results; as before, compared against white students, Black and Hispanic students are less likely to graduate when first enrolled in HBS or midrange schools. The primary difference is that Asian students are more likely to graduate when they matriculated to HBS than white student are. Midrange schools have somewhat lower graduation rates for all minority students.

Table 1B: Logistic Regression of Graduation Rate Allowing for Mismatch and Race-Based Barriers
Results Relevant to Race-Based Barriers Testing

Variable	ΔPr(Graduate) [18]	
	2007 Article	Revised Results
Student Race (compare to White) (Historically Black Schools)		
Comparison (Baseline) Probability	91.5%	93.3%
Black	-6.7%	-5.9%

[17] For these interaction terms, I provide only an overall likelihood ratio test to test the null hypothesis that all interactions are jointly equal to zero.
[18] This number provides the change in probability between the given characteristic and the control, holding all other factors at their median or modal value (LSAT = 37; UGPA= 3.3; Race=White).

Hispanic	-6.4%	-5.5%
Asian	-3.7%	2.9%
Student Race (compare to White) (Low Range Schools)		
Comparison (Baseline) Probability	90.9%	93.5%
Black	-1.5%	-0.9%
Hispanic	1.9%	1.5%
Asian	5.1%	3.7%
Student Race (compare to White) (Midrange Schools)		
Comparison (Baseline) Probability	91.7%	91.6%
Black	-3.5%	-3.6%
Hispanic	-1.1%	-1.2%
Asian	-1.5%	-1.5%
Student Race (compare to White) (Top 30 Schools)		
Comparison (Baseline) Probability	95.9%	94.8%
Black	0%	0.1%
Hispanic	-2.5%	-3.1%
Asian	0.6%	0.8%
Overall Race and School Type * Race Interactions (16 variables) p-value = 0.0025		

Tables 2A-2B reports results for the bar passage rate. [19] In Table 2A, testing mismatch, the results are significantly different from the 2007 article. First, there is no evidence of an anti-mismatch effect. Second the magnitudes of all effects are much smaller, particularly for HBS. Overall, the results demonstrate a similar pattern to Table 1A: for students with low credentials, those in HBS fair better than those in Midrange schools, while those students in Low range schools fair worse. Going to a Top 30 school with low credentials is also a riskier proposition. The revised results do not demonstrate the monotonic pattern indicative of the mismatch effect.

Table 2A: Logistic Regression of Bar Passage Rate Allowing for Mismatch and Race-Based Barriers
Results Relevant to Mismatch Testing

Variable	ΔPr(Pass Bar) [20]	
	2007 Article	Revised Results
Mismatch (compare to Midrange Schools) (Fixed student credentials at 5th percentile,)		
Comparison (Baseline) Probability	63.0%	73.7%
Historically Black Schools	-50.1%	4.2%
Low range Schools	-16.2%	-2.3%
Midrange Schools	--	--

[19] Because the focus of these results is on the number of lawyers created, the results include students who do not attempt to pass the bar as "non-passers", that is, not lawyers, and therefore not passing the bar is not necessarily a failure, but instead, either a failure or a choice to forgo the bar exam.

[20] This number provides the change in probability between the given characteristic and the control, holding credentials at the specified value and race at its modal value, white.

Top 30 Schools	1.7%	-9.5%
Mismatch (compare to Midrange Schools) (Fixed student credentials at 10th percentile)		
	73.8%	76.1%
Historically Black Schools	-46.8%	3.2%
Low range Schools	-15.1%	-1.7%
Midrange Schools	--	--
Top 30 Schools	1.9%	-7.9%
Mismatch (compare to Midrange Schools) (Fixed student credentials at 25th percentile)		
Comparison (Baseline) Probability	80.3%	86.0%
Historically Black Schools	-17.9%	-1.7%
Low range Schools	-9.1%	-0.4%
Midrange Schools	--	--
Top 30 Schools	3.5%	0.5%
Mismatch (compare to Midrange Schools) (Fixed student credentials at 50th percentile)		
Comparison (Baseline) Probability	84.8%	89.1%
Historically Black Schools	-7.6%	-1.4%
Low range Schools	-6.6%	-0.9%
Midrange Schools	--	--
Top 30 Schools	3.5%	2.5%
Overall School Type * Credentials Interactions (27 variables): p-value = 0.005		

Table 2B investigates race-based barriers in bar passage. Here, the results are not substantively different, although the magnitude of the changes is generally smaller. All minority groups are less likely to take and pass a bar exam from all schools except for low range schools; in those schools, Hispanic students are somewhat more likely to pass a bar exam.

Table 2B: Logistic Regression of Bar Passage Rate Allowing for Mismatch and Race-Based Barriers
Results Relevant to Race-Based Barriers Testing

Variable	ΔPr(Pass Bar) [21]	
	2007 Article	Revised Results
Student Race (compare to White) (Historically Black Schools)		
Comparison (Baseline) Probability	77.1%	87.7%
Black	-11.9%	-8.1%
Hispanic	-7.1%	-7.0%
Asian	-26.0%	-14.5%
Student Race (compare to White)		

[21] This number provides the change in probability between the given characteristic and the control, holding all other factors at their median or modal value (LSAT = 37; UGPA= 3.3; Race=White). Bar passage is defined as in Table 2A.

(Low Range Schools)		
Comparison (Baseline) Probability	78.1%	88.2%
Black	-7.7%	-4.8%
Hispanic	5.6%	2.7%
Asian	-0.8%	-1.1%
Student Race (compare to White) (Midrange Schools,)		
Comparison (Baseline) Probability	84.8%	89.1%
Black	-8.6%	-7.5%
Hispanic	-5.8%	-5.2%
Asian	-6.4%	-4.0%
Student Race (compare to White) (Top 30 Schools)		
Comparison (Baseline) Probability	88.3%	91.6%
Black	-0.9%	-1.7%
Hispanic	-1.6%	-3.5%
Asian	1.0%	-0.3%
Overall Race and School Type * Race Interactions (16 variables) p-value = 0.000		

Table 3A: Logistic Regression of Well Paying Job Rate,[22]
Allowing for Both Mismatch and Race-Based Barriers
Results Relevant to Mismatch Theory

Variable	ΔPr(High Salary) [23]	
	2007 Article	Revised Results
Mismatch (compare to Midrange Schools) (Fixed student credentials at 5th percentile,)		
Comparison (Baseline) Probability	6.1%	6.0%
Historically Black Schools	-5.0%	-5.5%
Low range Schools	-2.7%	2.0%
Midrange Schools	--	--
Top 30 Schools	2.4%	1.1%
Mismatch (compare to Midrange Schools) (Fixed student credentials at 10th percentile,)		
Comparison (Baseline) Probability	7.6%	6.7%
Historically Black Schools	-7.1%	-6.1%
Low range Schools	-2.3%	2.0%

[22] Prof. Sander notes that in my 2007 essay, I reported an unweighted population percentage for the percentage of students who obtained a well paying job. This was an error; using the weighted average is correct in this situation. This does not, however, affect the results of my logistic regression model, where using unweighted values is the most appropriate method. See Charles F. Manski & Daniel McFadden, Alternative Estimators and Sample Designs for Discrete Choice Analysis, in Structural Analysis of Discrete Data with Econometric Applications, (1981).

[23] This number provides the change in probability between the given characteristic and the control, holding credentials at the specified value and race at its modal value, white.

Midrange Schools	--	--
Top 30 Schools	2.1%	0.9%
Mismatch (compare to Midrange Schools) (Fixed student credentials at 25th percentile)		
Comparison (Baseline) Probability	9.6%	11.4%
Historically Black Schools	-9.4%	-8.5%
Low range Schools	-0.7%	-4.5%
Midrange Schools	--	--
Top 30 Schools	7.1%	1.4%
Mismatch (compare to Midrange Schools) (Fixed student credentials at 50th percentile)		
Comparison (Baseline) Probability	14.1%	14.0%
Historically Black Schools	-13.4%	3.3%
Low range Schools	-5.0%	-10.1%
Midrange Schools	--	--
Top 30 Schools	20.7%	6.4%
Overall School Type * Credentials Interactions (27 variables): p-value = 0.215		

Tables 3A-3B present the results of the logistic regression model which investigates the rate of reporting a well-paying job, defined as a job that pays more than $50,000 in 1995 dollars.[24] These results were not statistically significant – overall, the school type * credentials interactions were not different from zero. This was also true in the 2007 article. Thus, the results provide no evidence of a mismatch effect. One should note, however, that these data are particularly problematic, because there were a large number of students who chose not to answer this question.

Table 3B: Logistic Regression of Well Paying Job Rate,
Allowing for Mismatch and Race-Based Barriers
Results Relevant to Race-Based Barriers Testing

Variable	ΔPr(High Salary) [25]	
	2007 Article	Revised Results
Student Race (compare to White) (Historically Black Schools)		
Comparison (Baseline) Probability	0.7%	17.3%
Black	7.6%	56.4%
Hispanic	0.1%	2.9%
Asian	*	*
Student Race (compare to White) (Low Range Schools)		
Comparison (Baseline) Probability	9.1%	3.9%

[24] Prof. Sander notes out that the results are based upon the definition of "well-paying job" as a job that pays more than $50,000 per year, rather than the $40,000 per year stated in the 2007 essay. The results are essentially unchanged across the two cutoffs. Results with the $40,000 cutoff are available from the Northwestern Law Review. [CITE to website]

[25] This number provides the change in probability between the given characteristic and the control, holding all other factors at their median or modal value (LSAT = 37; UGPA= 3.3; Race=White).

Black	11.3%	5.5%
Hispanic	2.1%	1.0%
Asian	*	*
Student Race (compare to White) (Midrange Schools)		
Comparison (Baseline) Probability	14.1%	14.0%
Black	7.9%	8.2%
Hispanic	5.9%	6.0%
Asian	6.1%	6.1%
Student Race (compare to White) (Top 30 Schools)		
Comparison (Baseline) Probability	34.8%	20.4%
Black	29.7%	26.7%
Hispanic	9.7%	7.6%
Asian	6.3%	4.7%
Overall Race and School Type * Race Interactions (16 variables) p-value = 0.000		

* Insufficient variation in the data to estimate this parameter.

Finally, Table 3B provides the results of the race-based barriers theory on obtaining a well-paying job. All minority groups were more likely to report having obtained a well-paying job than their white counterparts. Black students, in particular, had *significantly higher* probability of obtaining a well-paying job. These differences are highly statistically significant overall, but the statistical significance does not take into account the potential for bias in the results due to non-response, or other reasons why minority students might search for a well-paying job more diligently than white students (for example, minority students have higher debt loads on average, making a well-paying job more of a necessity).

Overall, the results no longer support an anit-mismatch effect, magnitudes are generally smaller, and there is little evidence of a mismatch pattern across all school types.

Tables 4-6 combine the two possible effects – a mismatch effect with a race-based barriers effect -- for black law students and attempt to provide the best advice for these students: should they go to the best school to which they are admitted (the conventional wisdom), or should, as Professor Sander argues, they go to a lower-ranked school to avoid being outmatched by their classmates.

The results from the corrected model are more nuanced. For students with lower credentials, historically black schools and top 30 schools are the best choices. For students with better credentials, low range schools and top 30 schools are the best options, in terms of graduation rates. Bar passage rates, in contrast, suggest that the combination of all effects – particularly the stronger race-based barriers effect – suggests that students in the lowest credentials ranges should matriculate to a lower ranked school. This is not, however, just the mismatch effect; if it were, Table 2A would demonstrate a mismatch effect. Instead, it is the entire model, and the large differences in bar passage rates between whites and minority students with the same credentials (and therefore the same likelihood of being outmatched) that create the overall picture that black students have higher bar passage rates at lower ranked schools.

Table 4: Logistic Regression of Graduation Rate Allowing for Mismatch and Race-Based Barriers
Combination of Mismatch and Race-Based Barriers Theories for Black Students

Variable	Pr(Graduate) [26]	
	2007 Article	Revised Results
Fixed student credentials at 5th percentile		
Historically Black Schools	66.3%	84.0%
Low range Schools	68.5%	78.6%
Midrange Schools	77.0%	79.2%
Top 30 Schools	88.5%	86.6%
Fixed student credentials at 10th percentile		
Historically Black Schools	70.9%	84.8%
Low range Schools	74.4%	80.8%
Midrange Schools	82.2%	81.0%
Top 30 Schools	91.6%	87.4%
Fixed student credentials at 25th percentile		
Historically Black Schools	79.0%	86.7%
Low range Schools	82.6%	89.8%
Midrange Schools	85.4%	86.8%
Top 30 Schools	94.3%	93.0%
Fixed student credentials at 50th percentile		
Historically Black Schools	84.9%	87.4%
Low range Schools	89.4%	92.6%
Midrange Schools	88.1%	88.0%
Top 30 Schools	95.9%	94.9%

Table 5: Logistic Regression of Bar Passage Rate Allowing for Mismatch and Race-Based Barriers
Combination of Mismatch and Race-Based Barriers Theories

Variable	Pr(Pass Bar) [27]	
	2007 Article	Revised Results

[26] This number provides the change in probability between the given characteristic and the control for black students, holding credentials at the specified value.

[27] This number provides the change in probability between the given characteristic and the control for black students, holding credentials at the specified value.

Fixed student credentials at 5th percentile		
Historically Black Schools	7.6%	66.0%
Low range Schools	36.9%	62.8%
Midrange Schools	49.5%	60.4%
Top 30 Schools	62.7%	59.6%
Fixed student credentials at 10th percentile		
Historically Black Schools	17.0%	67.8%
Low range Schools	48.6%	66.2%
Midrange Schools	61.8%	63.3%
Top 30 Schools	74.1%	63.7%
Fixed student credentials at 25th percentile		
Historically Black Schools	48.0%	74.7%
Low range Schools	62.2%	80.0%
Midrange Schools	70.1%	76.9%
Top 30 Schools	82.6%	84.0%
Fixed student credentials at 50th percentile		
Historically Black Schools	65.2%	79.6%
Low range Schools	70.3%	83.4%
Midrange Schools	76.1%	81.6%
Top 30 Schools	87.3%	89.9%

Finally, Table 6 provides the same snapshot of results for the model of a well-paying job. Here, the results generally suggest that historically black schools and top 30 schools are the best choices for higher credentialed students, and low range schools and top 30 schools are the best choices for lower credentialed students.

Table 6: Logistic Regression of Well Paying Job Rate,
Allowing for Both Mismatch and Race-Based Barriers
Combination of Mismatch and Race-Based Barriers Theories for Black Students

Variable	Pr(Well Paying Job) [28]	
	2007 Article	Revised Results
Fixed student credentials at 5th percentile		
Historically Black Schools	12.7%	6.2%
Low range Schools	8.1%	18.3%
Midrange Schools	10.0%	10.1%
Top 30 Schools	24.0%	21.0%
Fixed student credentials at 10th percentile		
Historically Black Schools	6.1%	7.4%
Low range Schools	12.5%	19.5%
Midrange Schools	12.4%	11.1%
Top 30 Schools	26.8%	22.2%
Fixed student credentials at 25th percentile		
Historically Black Schools	3.2%	28.9%
Low range Schools	20.0%	16.0%
Midrange Schools	15.5%	18.5%
Top 30 Schools	40.5%	33.9%
Fixed student credentials at 50th percentile		
Historically Black Schools	8.3%	73.7%
Low range Schools	20.3%	9.4%
Midrange Schools	22.0%	22.2%
Top 30 Schools	64.5%	47.2%

The results of the simulations of alternative affirmative action policies depend on the specific model results from above. I present the revised results below. The primary question Tables 7-9 attempt to answer is a counterfactual: what would happen under different affirmative action policies, assuming that nothing else pertinent changes (for example, the culture of an institution or its applicant pool). Table 7 provides the results of 4 different affirmative action policies on the number of bar passers, and finds that the different policies would

[28] This number provides the change in probability between the given characteristic and the control for black students, holding credentials at the specified value.

have no statistically significant difference on the number of new black lawyers each year.[29] Similarly, Table 8 provides the results for the number of minority graduates. Again, there is no statistically significant difference across different affirmative action policies. Finally, Table 9 suggests that there may be one detriment for black law students under the no affirmative action policy: fewer well-paying jobs. Given the low response rate for this question, however, this result is suggestive only.

Table 7: Bar Passage Simulation For Three Different Models

Type of Admissions Policy	# White Bar Passers (se)	# Black Bar Passers (se)	# Hispanic Bar Passers (se)	# Asian Bar Passers (se)
Affirmative Action (Status Quo	19762 (73)	1141 (33)	972 (31)	906 (29)
No Affirmative Action (No boost for minority applicants)	19764 (73)	1134 (33)	986 (30)	905 (30)
Affirmative Action Light (1/2 the boost for minority applicants)	19762 (74)	1135 (33)	979 (31)	906 (29)
Affirmative Action Plus (2x the boost for minority applicants)	19761 (74)	1152 (33)	967 (30)	906 (29)

Table 8: Simulation of Number of Graduates, Using Three Different Models

Type of Admissions Policy	# White Graduates (se)	# Black Graduates (se)	# Hispanic Graduates (se)	# Asian Graduates (se)

[29] The four policies are "affirmative action" (the status quo), no affirmative action, in which minority applicants are admitted to institutions based on the probability that a white student with the same credentials would be admitted (this includes assuming that the bottom 14% of minority students would not matriculate to a law school); affirmative action "light", which provides only half the boost in admission rates that minorities currently receive, with 7% of minority students denied admission who would otherwise have matriculated to a law school; and affirmative action "plus", which provides twice the boost that minority applicants received. Prof. Sander points out in his response that I assume that 14% of underrepresented minority students, rather than 14% of Black students, would not matriculate to law schools absent affirmative action. The results remains essentially the same using only Black students. Results are available from the Northwestern Law Review. [CITE to website]

Affirmative Action (Status Quo	20428 (71)	1481 (37)	1112 (32)	988 (30)
No Affirmative Action (No boost for minority applicants)	20430 (71)	1459 (37)	1118 (32)	988 (31)
Affirmative Action Light (1/2 the boost for minority applicants)	20429 (71)	1466 (37)	1115 (32)	988 (30)
Affirmative Action Plus (2x the boost for minority applicants)	20428 (71)	1499 (38)	1110 (32)	988 (30)

Table 9: Simulations of Graduates with Well-Paying Jobs

Type of Admissions Policy	# White Job Takers (se)	# Black Job Takers (se)	# Hispanic Job Takers (se)	# Asian Job Takers (se)
Affirmative Action (Status Quo	4616 (61)	310 (18)	236 (16)	252 (16)
No Affirmative Action (No boost for minority applicants)	4612 (63)	265* (16)	220 (15)	252 (16)
Affirmative Action Light (1/2 the boost for minority applicants)	4616 (63)	284 (16)	227 (16)	252 (16)
Affirmative Action Plus (2x the boost for minority applicants)	4615 (62)	340 (19)	248 (15)	252 (16)

* Statistically significant (as compared with status quo) at 0.05 level

Conclusion

The revised results present a different picture of student outcomes. The data do not support the anti-mismatch effect any more than they support the mismatch hypothesis. When I originally began this project six years ago, one goal I had was to incorporate the large amount of uncertainty in the data regarding the results of Professor Sander's article. This was the impetus for the simulations in Part III of the original essay, and the discussion of possible experimental data in Part IV. However, the (erroneous) results I found were strikingly different from Professor Sander's, and the focus of the essay shifted. While the revised results demonstrate a more nuanced picture of student outcomes, the underlying uncertainty of the data remains. Sometimes in order to answer key empirical questions one must obtain better data. I advocated for this in my original 2007 article. I take this brief opportunity to advocate for it again here. While the data can provide clues regarding whether mismatch or a race-based barriers theory might explain the difference in some outcomes between black and white students, the data, simply put, is not up to the task of definitively determining the cause of outcome differences.

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