AccessLex

BAR EXAM SUCCESS ANALYSES

FINAL REPORT FOR RUTH BADER GINSBURG SCHOOL OF LAW

This report is for demonstration purposes only. Ruth Bader Ginsburg School of Law is a fictitious institution and the data used do not apply to any one particular institution. As such no inferences nor conclusions should be drawn based on the information reported herein.

JANUARY 2024

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1. BACKGROUND AND APPROACH

The AccessLex Bar Exam Success Analysis Initiative examines the extent to which academic factors among recent graduates are correlated with, and predictive of, law school academic performance and first-time bar exam passage. In this report, we utilize transcript and bar exam data obtained from your institution to examine the relationships between bar exam performance and (1) law school GPA (LGPA), (2) credits and grades earned in particular coursework, and (3) preadmission factors. We also explore the extent to which LSAT score, undergraduate GPA (UGPA), and UGPA growth predict LGPA.

These analyses are designed to help your school more effectively identify students at risk of low academic performance and failing the bar exam. In addition, this report is intended to help identify for whom and when intervention would be most beneficial, and to provide data that can be used to advance new or ongoing student success initiatives.

A. Data and Demographic Statistics

Ruth Bader Ginsburg (RBG) Law submitted de-identified demographic and academic data for 4,078 students who matriculated in 2012 through 2019. Of the 4,078 individuals, none were dismissed, 35 transferred in, and none transferred to another school (see Table 1).

TABLE 1

SAMPLE CHARACTERISTICS

	2012–2019 Entering Cohorts	
	Count[1]	**Percent[2]**
Gender		
Female	1,769	43
Male	1,569	38
Race/Ethnicity		
Black	334	8
Hispanic	617	15
White	1,881	46
Remaining	374	9
Enrollment		
Transfer (Out)	0	0
Transfer (In)	35	< 1
First Generation Student		
Yes	185	4
No	3,893	96
First-Time Bar Passage		
Pass	2,971	73
Fail	1,107	27
Total	4,078	–

Notes: [1]Totals may not add to 4,078 due to missing data.
[2]Totals may not add to 100 due to rounding or missing data.

B. Analytical Approach

As noted above, this report aims to identify predictors of LGPA and bar exam performance. Predictors of each are summarized separately in the results that follow.

For the analyses of first-year law school performance, we construct OLS linear regression models to examine the extent to which various factors, such as a student's highest LSAT score, final UGPA, and UGPA growth, explain a student's first-year (1L) LGPA.

For the analyses of bar passage (pass or fail), we construct logistic regression models and examine the extent to which the following factors are predictive of first-time bar exam result: 1L LGPA; LGPA growth; credit hours earned in doctrinal, skill- and clinic-based, legal writing, and externship courses; LGPA in specific doctrinal courses; LSAT score; final UGPA; and UGPA growth. We report the results as changes to a student's predicted probability of passing the bar exam.

The size of a predictive effect refers to the size of the increase in predicted outcome (e.g., probability of passing the bar exam) when the independent variable (e.g., 1L LGPA) increases from its minimum to maximum value. We classify effects as null, small, medium, or large based on the criteria as shown below. These classifications are intended to provide context regarding *practical* significance of the findings and are independent of *statistical* significance.

If a change in the predictor variable (e.g., final UGPA, LSAT score) from its minimum to maximum value is associated with a…	*1L LGPA change of*		*Change in predicted probability of bar passage of*	*the effect is:*
	Less than 0.52 points	*Or*	10 or fewer percentage points	**Null** (or negligible)
	0.53–1 point	*Or*	11–30 percentage points	**Small** (or modest)
	1.1–2 points	*Or*	31–50 percentage points	**Medium** (or moderate)
	More than 2 points	*Or*	More than 50 percentage points	**Large** (or substantial)

2. RESULTS

A. What Predicts Law School Performance?

We begin by investigating the determinants of academic performance. To do this, we examine the relationships between 1L LGPA (the outcome variable) and two preadmission variables: highest LSAT score and final UGPA. For these analyses, we create one model, which includes its own set of control variables—factors that are statistically related to both 1L LGPA and the preadmission variable(s) in the model. For example, we would include a control variable for age if we found evidence of a relationship between it, 1L LGPA, and either LSAT score or final UGPA.

In each case, we consider the following control variables: race, gender, age, first-generation student status, selectivity of undergraduate institution (i.e., acceptance rate), years to complete undergraduate degree, LSAT score, final UGPA, UGPA growth, undergraduate major (including whether a student dual-majored while in college), year of first bar exam attempt, month of first bar exam attempt, and transfer during college or law school.

i. LSAT Score and UGPA

We find that highest LSAT score and final UGPA are associated with higher 1L LGPAs, to varying degrees. This model controls for students' race, gender, and age and the selectivity of their undergraduate institution.

Specifically, we find that:

An increase in highest LSAT score from the mean (153 at RBG Law) by:

- **One point** (to 154) is associated with a **0.03-point increase** in 1L LGPA.
- **Six points** (to 159; approximately one standard deviation) is associated with a **0.22-point increase** in 1L LGPA.

An increase in final UGPA from the mean (3.27) by:

- **One-tenth of a point** (to 3.37) is associated with a **0.02-point increase** in 1L LGPA.
- **One-half of a point** (to 3.77; approximately one standard deviation) is associated with a **0.12-point increase** in 1L LGPA.

ii. UGPA Growth

We also consider other transcript data that could help identify students with greater propensity for early academic success in law school. Previous AccessLex Institute reports identified a strong, positive relationship between LGPA growth (the difference between a student's first-semester LGPA and their final LGPA) and bar passage and early results indicate that UGPA growth (the difference between a student's first year and final UGPA) is associated with 1L LGPA.[1] We, therefore, investigate the relationship between UGPA growth and 1L LGPA at RBG Law. For these analyses, we include in the model the students' first year UGPA in order to account for their starting place. Furthermore, we also control for students' race and gender.

Most notably, ***we find that UGPA growth has a positive relationship with 1L LGPA***. Holding all else constant, a student with a below average first-year UGPA who improves their UGPA by 0.1 grade points (the average at RBG Law) from the first year to the final year of their undergraduate studies is predicted to have a 1L LGPA 0.03 grade points higher than a similar student whose UGPA does not change and 0.1 grade points greater than a student whose UGPA diminished by 0.1 grade points.

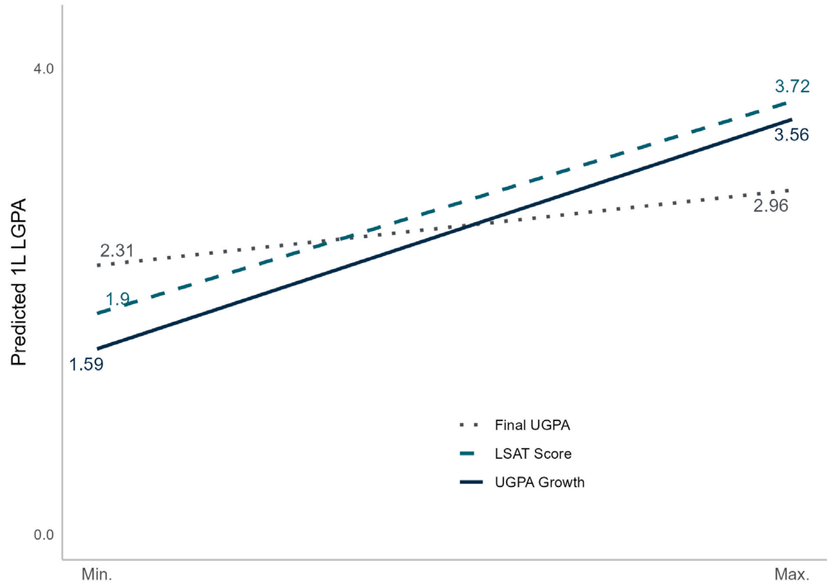
Figure 1 shows the effect that UGPA growth has on 1L LGPA, relative to that of LSAT score and final UGPA, for an individual with an average first-year UGPA. (The effects of growth for those with above average and below average first-year UGPAs are similar.) The dark blue solid line represents UGPA growth, the dashed gray line represents highest LSAT score, and the dotted gray line represents final UGPA. The steeper the slope of the line, the larger the effect.

As indicated by the steepness of the slopes of the lines in Figure 1, our analyses find that UGPA growth (indicated by the blue line), regardless of the student's first-year UGPA, performs as well as or better than both LSAT score and final UGPA as a predictor of academic success in the first year of law school.

[1] In a previous report, we find that LGPA improvement during law school is associated with greater odds of passing the bar exam, particularly among students who struggle the most during the first semester; Taylor, A. N., Scott, J. M., & Jackson, J. L. (2021). "It's not where you start, it's how you finish: Predicting law school and bar success." *Journal of Higher Education Theory & Practice*, *21*(10). https://www.proquest.com/openview/013929c81e0a389d3c0a7afe37da7bf2/1?pq-origsite=gscholar&cbl=766331

FIGURE 1

UGPA GROWTH PREDICTS 1L LGPA AS WELL AS HIGHEST LSAT SCORE AND BETTER THAN FINAL UGPA



B. What Predicts First-Time Bar Exam Performance?

In this section, we investigate determinants of bar performance by examining the relationships between first-time bar passage and several other factors.

For these analyses, we create several models, each of which includes its own set of control variables—factors that are statistically related to *both* bar performance *and* the variable(s) of interest in the model. For example, we would include a control variable for age if we found evidence that it is related to both bar performance and 1L LGPA. This means that these analyses account for other factors that could have an impact on bar performance and its predictors, so the results that follow hold true even when other student characteristics, such as matriculation year and race, vary.

Since the predictor variables are different in each model, the control variables utilized may also differ. If a control variable is included in one model but not in another, it means that variable had the requisite statistical relationships with the outcome and predictor variables in one model but not the other. In each case, we consider the following control variables: race, gender, age, first-generation student status, selectivity of undergraduate institution (i.e., acceptance rate), time to undergraduate degree completion, highest LSAT score, final UGPA, UGPA growth, undergraduate major (including whether a student dual-majored while in college), year of first bar exam attempt, month of first bar exam attempt, and transfer during college or law school.

i. 1L LGPA

We first consider the effect of 1L LGPA on first-time bar passage. We find that ***higher 1L LGPAs are associated with greater likelihood of first-time bar passage, and that this relationship is statistically significant.*** A student with a 1L LGPA of 2.91 (the average 1L LGPA) has a predicted likelihood of first-time bar passage that is 30 percentage points higher than a student with a 2.39 1L LGPA (one standard deviation below the average).

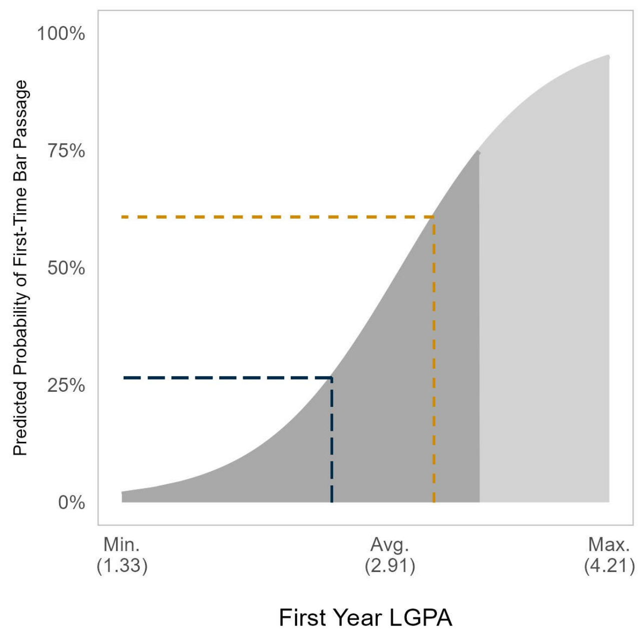
Figure 2 shows the predicted likelihood of first-time bar passage based on 1L LGPA, holding constant race, gender, age, and law school graduation year.

The effect is largest for students whose 1L LGPAs fall below 3.45 grade points, where the line's slope is steepest. Within this area, even a modest increase in LGPA is associated with marked increases in predicted probability of first-time bar passage. Beyond this area, the curve of the line begins to plateau, which means that even large increases in LGPA are associated with only slight increases in predicted probability of first-time bar passage.

Consequently, students with LGPAs falling below 3.45 grade points (the dark gray area in Figure 2) have the greatest opportunity to increase their chances of first-time bar passage through LGPA improvement, and therefore would likely benefit most from academic intervention.

FIGURE 2

THE LIKELIHOOD OF FIRST-TIME BAR PASSAGE INCREASES AS 1L LGPA INCREASES, WITH THE GREATEST GAINS AMONG STUDENTS BELOW A 3.45 1L LGPA



To demonstrate the importance of 1L LGPA within these ranges in Figure 2, we indicate the differences in predicted probability of first-time bar passage for two different students. The blue dashed line represents a student with a 1L LGPA at the 25th percentile (2.57) and the yellow dashed line represents a student with a 1L LGPA one-half a standard deviation above the average (3.17). The space between where the two lines meet the y-axis is the increase in predicted probability of first-time bar passage (a difference of 34 percentage points.

ii. LGPA Growth

In addition to analyzing 1L LGPA, we examine the extent to which LGPA growth—the difference between a student's first-semester (1S) and final LGPA—is associated with first-time bar performance, holding age, race, and law school graduation year constant. In this model, we also control for 1S LGPA to account for a student's starting place.

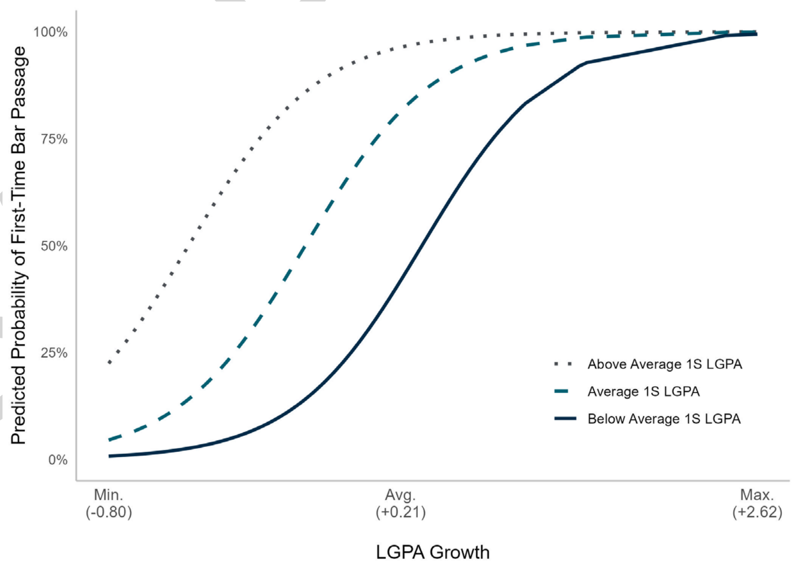
We find that ***positive growth is associated with greater predicted likelihoods of passing the bar*** and that negative growth (or a decrease in LGPA) is associated with lower predicted likelihoods.

Figure 3 shows how a student's predicted probability of first-time bar passage changes based on their LGPA growth and 1S LGPA. The blue line represents a student with below average 1S LGPA, the dashed teal line represents a student with average 1S LGPA, and the gray dotted line represents a student with above average 1S LGPA.

As evidenced by the steepness of the slopes of the lines, ***the influence of LGPA growth is especially notable among students with average 1S LGPAs*** (dashed teal line). Among these students, one who improves their LGPA (moves to the right along the x-axis) by just 0.21 grade points — the average increase for your students — from their first semester to graduation is predicted to have a probability of first-time passage 15 percentage points higher than a student whose LGPA did not grow, and 21 percentage points greater than a student whose LGPA decreases by 0.1 grade points.

FIGURE 3

REGARDLESS OF 1S LGPA, LGPA GROWTH IS ASSOCIATED WITH HIGHER PREDICTED PROBABILITIES OF BAR PASSAGE



LGPA growth is also important for students with below average 1S LGPAs; however, larger growth is needed to markedly improve their probability of passing the bar exam. Holding all else constant, a student with a below average 1S LGPA (solid blue line) who increases their LGPA from the first semester to graduation by 0.21 grade points has a predicted probability of first-time bar passage 5 percentage points greater than a student with no growth, and 7 percentage points greater than a student whose LGPA declines by 0.1 grade points.

LGPA growth is most important in the first year of law school as impactful changes in LGPA become more difficult to attain as the number of courses completed grows. Notwithstanding, there remain opportunities to encourage improvement after the 1L year.

iii. LGPA in Doctrinal Courses

In this section, we examine the effect of doctrinal (i.e., rule-based and often bar-tested law) LGPA on a student's predicted probability of first-time bar passage. We do this by examining LGPA in both overall doctrinal coursework (i.e., rule-based and often bar-tested law), as well as in one each of the following courses: Article 9 (Secured Transactions), Business Associations, Criminal Procedure, Evidence, Family Law, and Trusts and Estates. (See Table 3 for coursework descriptions.)

On average, we find that ***doctrinal LGPA—overall and in each course—has a consistently positive effect on bar passage***. Furthermore, these effects are statistically significant.

Overall doctrinal LGPA (measured across all doctrinal courses) has the strongest relationship with bar passage. Students with a doctrinal course LGPA 0.48 grade points lower than the average (2.47 versus 2.95 at RBG Law) have a predicted probability of first-time bar passage 35 percentage points greater (48 versus 85 percent).

Figure 4 illustrates the extent to which the predicted probability of first-time bar passage changes in relation to LGPA for each doctrinal course we examined, comparing the predicted probability of bar passage for students with three different LGPAs: the average LGPA in a particular course and one standard deviation above and one standard deviation below the average.

For each of the doctrinal courses below (arranged by size of the relationship, from strongest to weakest), we compare the predicted probability of first-time bar passage of two students, one with an average course LGPA and one with a below average course LGPA. We find that:

> **Evidence *has a positive effect on bar passage.*** A student with an LGPA of 3.06 has a probability of first-time bar passage 25 percentage points higher than a student with a 2.37 LGPA.
>
> **Criminal Procedure *has a positive effect on bar passage.*** A student with an LGPA of 3.06 has a probability of first-time bar passage 21 percentage points higher than a student with a 2.59 LGPA.
>
> **Trusts and Estates *has a positive effect on bar passage.*** A student with an LGPA of 2.96 has a probability of first-time bar passage 20 percentage points higher than a student with a 2.33 LGPA.
>
> **Article 9 *has a positive effect on bar passage.*** A student with an LGPA of 3.13 has a probability of first-time bar passage 19 percentage points higher than a student with a 2.47 LGPA.

Business Associations *has a positive effect on bar passage.* A student with an LGPA of 3.23 has a probability of first-time bar passage 18 percentage points higher than a student with a 2.63 LGPA.

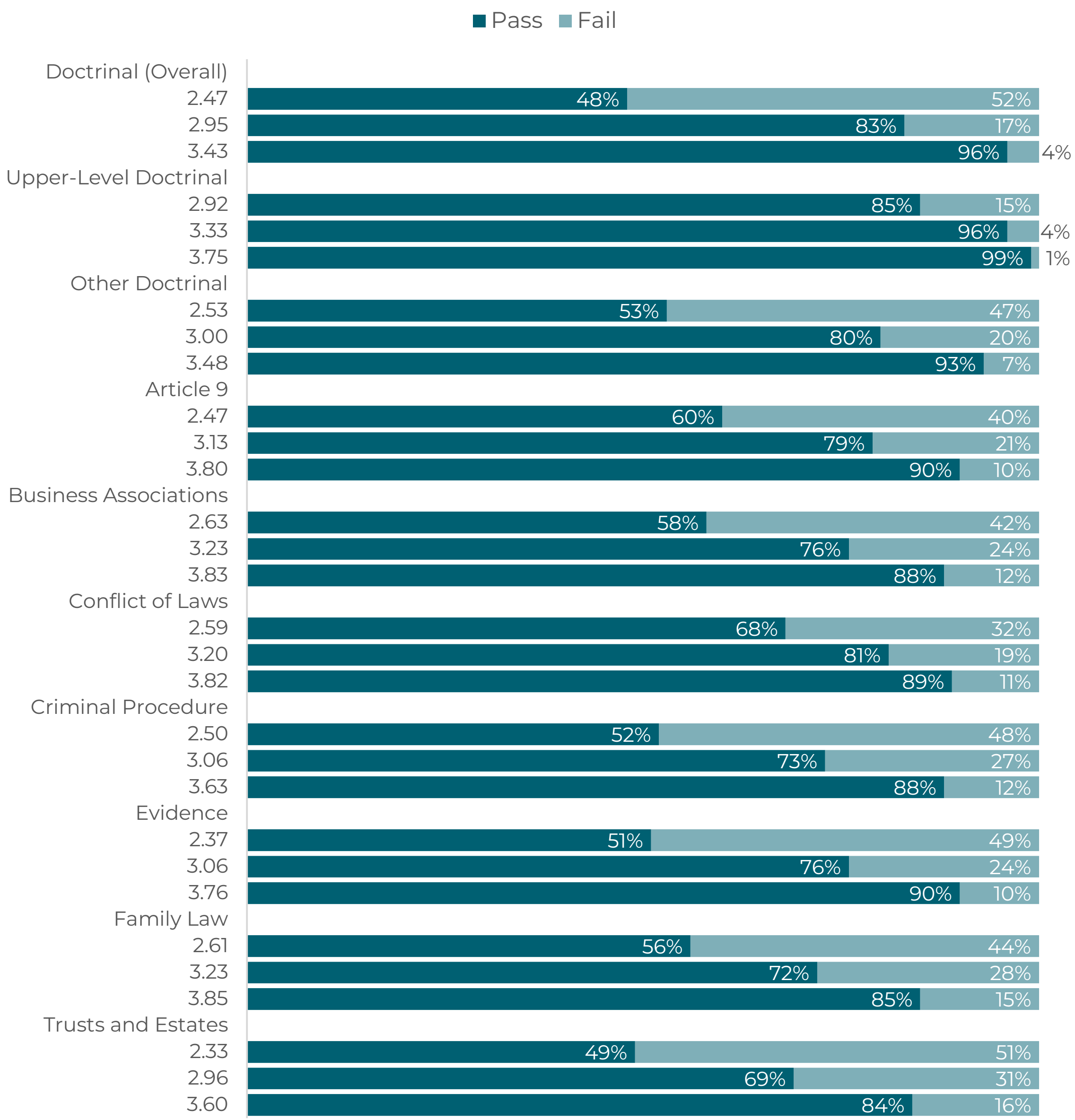
Family Law *has a positive effect on bar passage.* A student with an LGPA of 3.23 has a probability of first-time bar passage 16 percentage points higher than a student with a 2.61 LGPA.

Conflict of Laws *has a positive effect on bar passage.* A student with an LGPA of 3.20 has a probability of first-time bar passage 13 percentage points higher than a student with a 2.50 LGPA.

Looking across all doctrinal courses not specifically listed above (see "Other Doctrinal Courses" in Table 3), a student with an LGPA of 3.00 has a probability of first-time bar passage 27 percentage points higher than a student with a 2.53 LGPA.

FIGURE 4

THE PREDICTED PROBABILITY OF BAR PASSAGE INCREASES AS DOCTRINAL COURSE LGPA INCREASES



Note: LGPA values represent one standard deviation below the mean, at the mean, and one standard deviation above the mean for each course type.

iv. *Credit Hours in Doctrinal, Skill-based, Legal Writing, Clinic-based, Externship, and Other Elective Courses*

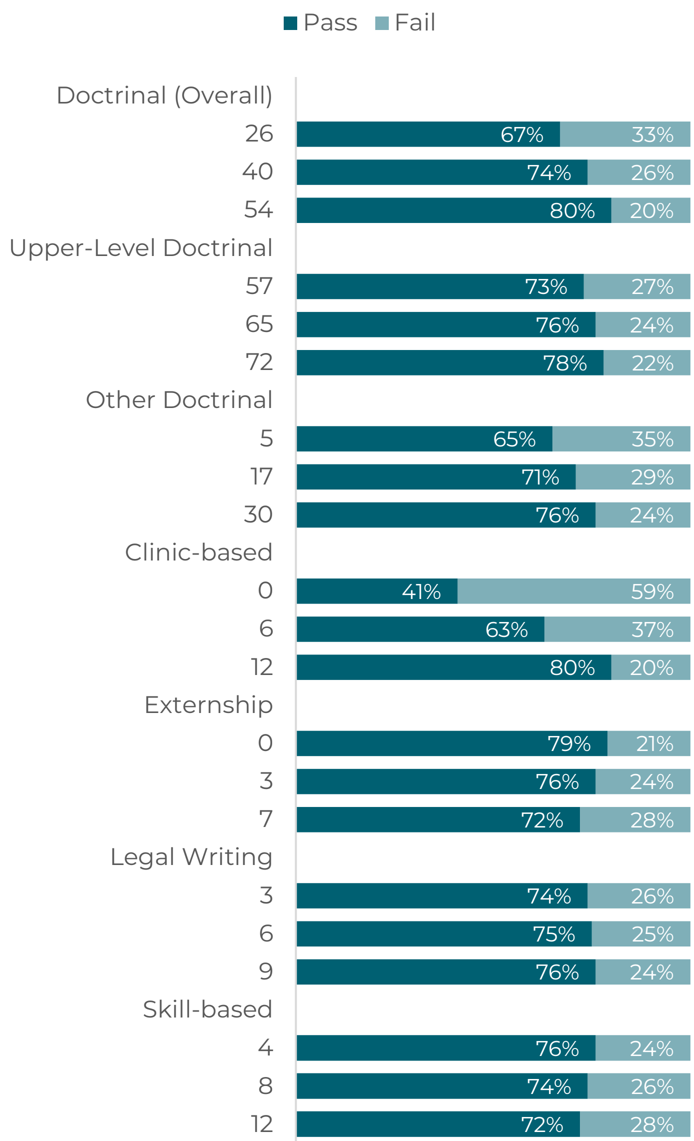
In this section, we examine the extent to which course credits earned in clinic- and skill-based courses, doctrinal courses, externships, legal writing courses, and other elective courses predict first-time bar passage. These models control for race, 1L LGPA, and law school graduation year.

Overall, we find that additional credit hours in clinic-based, legal writing, and doctrinal courses are associated with greater likelihoods of first-time bar passage. For externships and skill-based courses, we find that the number of credit hours is associated with decreased bar passage. **This does not mean that these courses are harming the probability of first-time bar passage, rather, it may be attributable to the nature of the bar exam itself.** The exam in its current form focuses on knowledge and memorization, while externships and skills-based courses teach law students practicable skills. The skills taught in these courses may not substantially affect one's ability to pass the bar, yet they remain important when it comes to practicing law.

As with Figure 4, Figure 5 illustrates the extent to which changes in earned credit hours in each of the course types listed in Table 3 (p. 23) relate to the probability of first-time bar passage. All of the credit hours results are statistically significant, except for externships and legal writing.

FIGURE 5

THE PREDICTED PROBABILITY OF BAR PASSAGE TENDS TO INCREASE WITH CREDIT HOURS EARNED IN DOCTRINAL AND SKILL-BASED COURSES



v. LSAT Score and UGPA

Below, we examine the extent to which LSAT score and UGPA predict first-time bar performance, holding age, race, and law school graduation year constant. We then contextualize the size of these effects by comparing them with those achieved when using LGPA to predict first-time bar passage.

We find that highest LSAT score has a positive effect on predicted probability of bar passage. Compared to a student with a highest LSAT score of 153 (the average), one with a score:

- **One point** (to 154) higher has a predicted probability of first-time bar passage **2 percentage points greater**.
- **Six points** (approximately one standard deviation; to 159) higher has a probability of first-time bar passage **12 percentage points greater**.

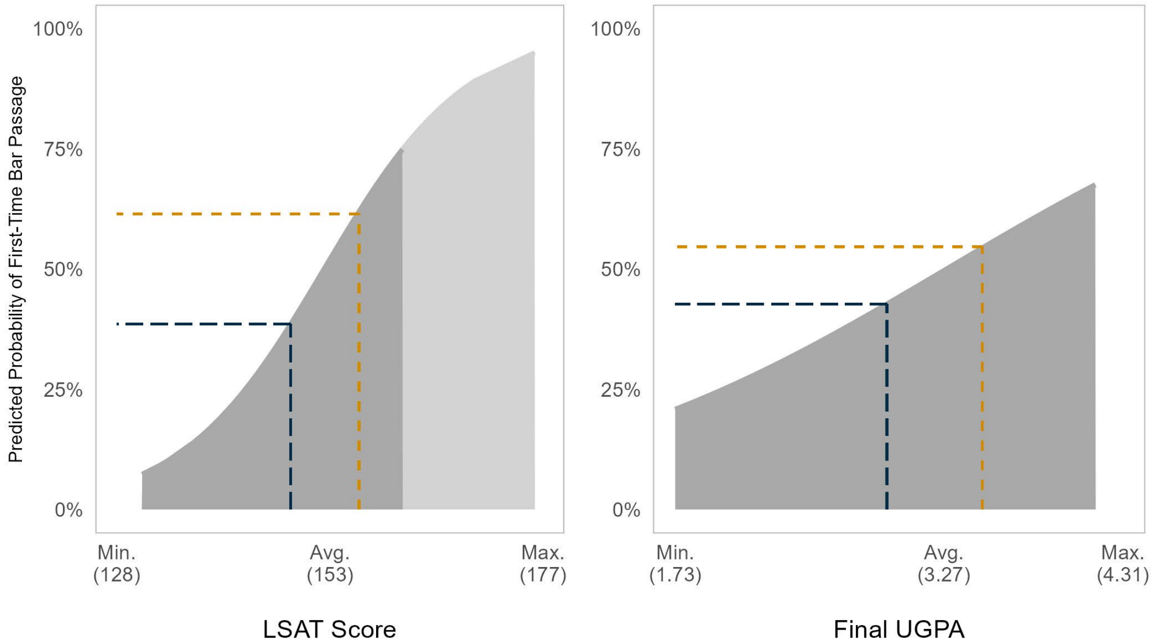
The impact of final UGPA on bar passage is positive. Compared to a student with a final UGPA of 3.27 (the average), one with a UGPA:

- **One-tenth of a point** (to 3.37) higher has a probability of first-time bar passage **2 percentage point greater**.
- Half of a point (approximately one standard deviation; to 3.77) has a probability of first-time bar passage **9 percentage points greater**.

In Figure 6 (as with Figure 2), we demonstrate the differences in predicted probability of first-time bar passage for two different students. The blue dashed line represents a student with an LSAT score or final UGPA at the 25th percentile (148 and 2.95, respectively) and the yellow dashed line represents a student a half standard deviation above the average (157 and 3.51, respectively). The space between where the two lines meet the y-axis is the increase in predicted probability of first-time bar passage. Represented by the dark gray area under the curve in Figure 6, the effects of LSAT score and UGPA are largest for students with a highest LSAT score below 161. There does not appear to be a cutoff point wherein an increase in UGPA is no longer beneficial for students' predicted probability of first-time bar passage.

FIGURE 6

PREDICTED PROBABILITY OF FIRST-TIME BAR PASSAGE INCREASES AS UGPA AND HIGHEST LSAT SCORE INCREASE



It is important to note that ***each LGPA variable, including LGPA growth, has a greater measurable influence on bar passage than LSAT score or final UGPA.*** This indicates that bar success is not predetermined; the coursework, faculty, and support services at RBG Law play a critical role in preparing students for success on the bar.

vi. UGPA Growth

Next, we examine whether other information contained in a student's admission profile might be predictive of bar success. Given our findings pertaining to LGPA growth above, which are consistent with previous AccessLex Institute reports,[2] we focus here on whether UGPA growth, measured as the difference between a student's first-year and final UGPA, can be used to predict a student's likelihood of first-time bar exam passage and bar exam score. As we do with LGPA growth, we account for the student's starting place in these analyses, and for the following control variables: age, race, and law school graduation year.

[2] In our report, "It's Not Where You Start, It's How You Finish," we find that GPA improvement during law school is associated with greater odds of passing the bar exam, particularly among students who struggle the most during the first semester.

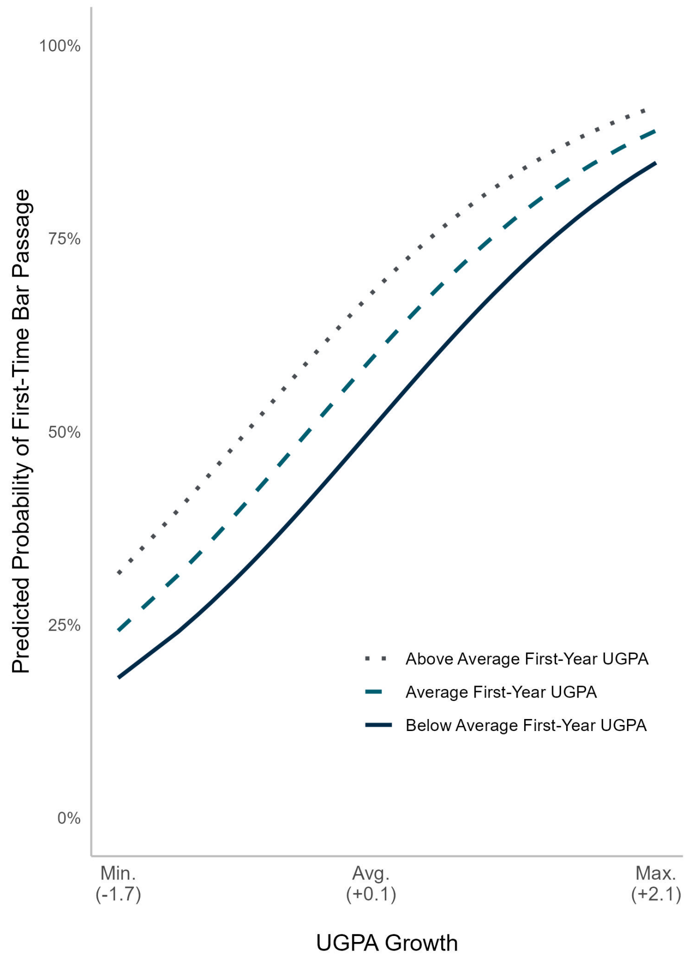
We find that ***as UGPA growth increases, so too does the predicted probability of first-time bar passage***. For negative UGPA growth, the predicted probability of passage decreases.

Figure 7 illustrates the extent to which changes in a student's UGPA growth are associated with changes in their predicted probability of first-time bar passage. The blue, teal, and gray lines represent students with below average, average, and above average first-year UGPAs, respectively.

Holding all else constant, a student with a below-average first-year UGPA (blue line) who improves their UGPA (moves to the right on the x-axis) by 0.1 grade points (approximately the average for Ruth Bader Ginsburg Law students) from the first year to the final year of their undergraduate studies is 3 percentage points more likely to pass the bar on their first attempt than a similar student whose UGPA does not change and 6 percentage points more likely than a student whose UGPA diminished by 0.1 grade points.

FIGURE 7

POSITIVE UGPA GROWTH IS ASSOCIATED WITH INCREASED PREDICTED PROBABILITY OF FIRST-TIME BAR PASSAGE, IRRESPECTIVE OF STARTING UGPA



C. A More Equitable Approach to Admission Review?

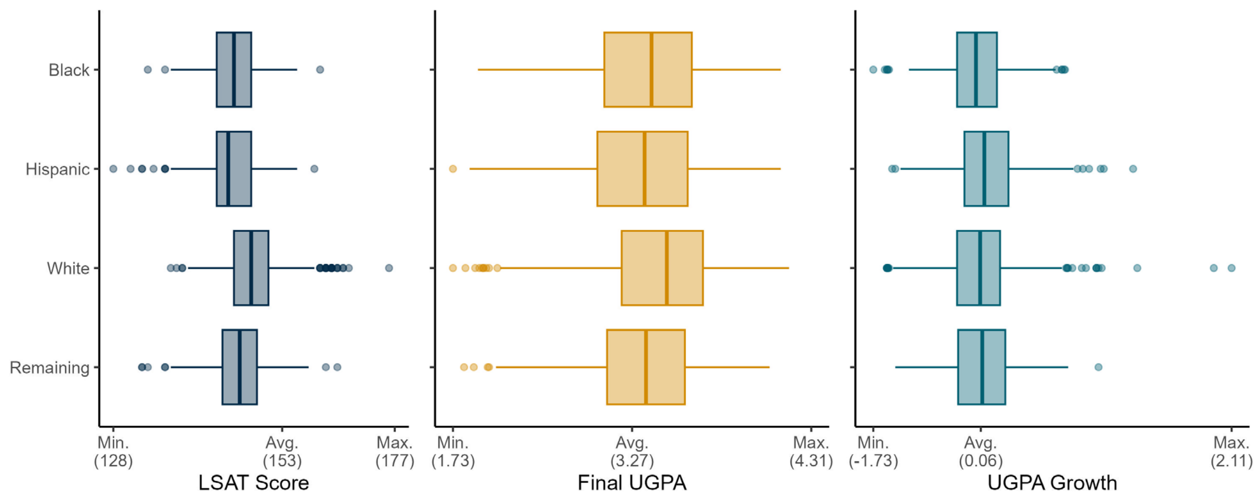
Given our finding that UGPA growth predicts early academic performance and bar success as well as or better than highest LSAT score and final UGPA, we explore how racial differences in these three preadmission factors compare.

Figure 8 illustrates the distribution of highest LSAT scores, final UGPAs, and UGPA growth values for Black, White, and all remaining racial/ethnic groups at Mercer Law. The box represents the middle 50 percent of the observed values, with the 25th percentile on the left and the 75th percentile to the right. Each box is intersected by a line that indicates the median, or the value at which 50 percent of the observations fall below and 50 percent of the observations lie above.

As shown in Figure 8, among those 4,078 students in our sample who matriculated in 2012–2019, White students had higher median LSAT scores and final UGPAs than their Black peers. Among those included in this study, White students have a median LSAT score of 152 and final UGPA of 3.23, compared to 149 and 3.11 for Black students, respectively. On the other hand, the variation in median UGPA growth values between White and Black students is 0.05 grade points. As with the median values, the bounds of the middle 50 percent of the data (the boxes) are nearly identical between the two groups.

FIGURE 8

THE MEDIAN AND MEAN UGPA GROWTH VARY LESS ACROSS RACIAL/ETHNIC GROUPS RELATIVE TO LSAT SCORE AND FINAL UGPA



3. SUMMARY AND RECOMMENDATIONS

This report offers insights regarding the factors most influential to academic performance and bar passage at Ruth Bader Ginsburg Law. Most notably, we find that:

- All LGPA measures—1S LGPA, 1L LGPA, and LGPA growth—are strong predictors of bar performance.
- LGPA improvement from the first semester to the end of law school is important for increasing a student's likelihood of bar passage.
- LGPA in doctrinal courses overall as well as in those we studied (i.e., Article 9, Business Associations, Conflict of Laws, Criminal Procedure, Evidence, Family Law, Trusts and Estates), are important indicators of future bar success.
- Additional credit hours in doctrinal courses have a substantial impact on first-time bar passage.
- LSAT score and UGPA are predictive of law school performance and first-time bar passage.
- UGPA growth is comparable to LSAT score and UGPA as a predictor of both law school performance and first-time bar passage, and it is associated with fewer racial disparities.

Based on these findings, we propose the following recommendations at Ruth Bader Ginsburg Law:

- **Properly contextualize pre-admission factors when making admission decisions.** Our results demonstrate that LSAT score and UGPA are positively correlated with 1L LGPA. However, these incoming academic indicators become less predictive of academic performance and bar passage over time and are weaker predictors of 1L LGPA than UGPA growth. This suggests that although LSAT score and UGPA are relevant, they are not determinative of academic and bar success. What happens in law school matters.
- **Consider UGPA growth as an admission factor.** Our analyses of Ruth Bader Ginsburg Law School graduates found UGPA growth to be comparable to LSAT score and UGPA as a predictor of both law school performance and first-time bar passage. Moreover, UGPA growth was not associated with the intense racial/ethnic disparities observed with LSAT score and UGPA. Taken together, these findings suggest that UGPA growth is a useful, equitable, and inclusive metric for evaluating applicants for admission to Ruth Bader Ginsburg Law School.
- **Encourage students to complete additional clinic-based and doctrinal courses (i.e., Article 9, Business Associations, Conflict of Laws, Criminal Procedure, Evidence, Family Law, Trusts and Estates).** Our findings demonstrate that the largest return on investment for students stems from increases in credit hours earned in these courses—taking an additional one of these courses is associated with an increase in likelihood of bar passage.

- **Foster and cultivate a "growth mindset" among faculty and students.** Our results indicate that not only is 1L LGPA an important factor in predicting first-time bar exam passage, but that a student's ability to improve their LGPA over time is more influential than 1S or 1L LGPA alone. LGPA growth is incredibly influential during the first year of law school. Focusing on supporting at-risk students and helping them grow and maintain higher LGPAs during year one (and beyond) may be one of the best intervention strategies for increasing bar passage rates. Although such early interventions stand the best chance of maximizing law students' potential, student ability is never fixed. Later and ongoing interventions in the 2L and 3L years, particularly when utilizing bar-tested doctrinal subjects, continue to be a worthwhile use of resources.
- **Continue to track LGPA across each year of law school to target interventions toward students with lower likelihood of first-time bar passage.** 1S LGPA, 1L LGPA, and LGPA growth are all influential for predicting bar passage outcomes and can help indicate when and where to target academic and bar success interventions.
- **Utilize 1S and 1L LGPA as a benchmark for bar success.** A law student at Ruth Bader Ginsburg Law School who earns a 3.36 LGPA in their first semester of law school has a 75% chance of first-time bar passage. This benchmark LGPA increases at the conclusion of the 1L year to a 3.45 LGPA. This demonstrates the need to direct interventions toward students who fall below these benchmarks in their first and second semesters of law school. Targeting early interventions at each critical juncture of students' progression through law school may help struggling students develop the necessary academic skills, leading to improvement in their LGPA, and in turn better chances of bar passage.

4. METHODOLOGY

A. Data

As noted above, your institution provided student data for 4,078 students who matriculated in 2012–2019, which include information related to their:

- First-semester, first-year, and final LGPA
- First-semester, first-year, and final class rank
- Credit hours in clinic and doctrinal courses, and enrollment in skills courses
- Number of bar exam attempts, exam scores, and exam passage
- Bar exam date and jurisdiction
- Matriculation year
- Undergraduate institution and major
- UGPA
- LSAT score
- Race
- Gender
- First-generation student (yes/no)
- Transfer-student status (college and law school)

B. Models

In our analyses, we use two methods of regression: OLS linear regression to examine the predictors of 1L LGPA; and logistic regression to investigate the predictors of first-time and ultimate bar passage.

i. Explanation of Linear Regression

We use OLS linear regression to analyze the relationships between predictor variables (see below) and LGPA. Linear regression is an appropriate choice when the outcome, in this case LGPA, is continuous or, even in many cases, discrete (that is, it can take on a finite number of values). Although the values that may be assigned for LGPA are finite, they vary sufficiently widely to be used in this manner.

Linear regression modeling produces a result called a coefficient, which is directly interpretable. For example, a linear regression coefficient might be used to measure the predicted impact of a one-point increase in a student's LSAT on their 1L LGPA. This means that the results from these regression models provide an intuitive and therefore useful means for inferring information about the relationships between two or more variables.

Greater discussion of linear regression and the interpretation of its outputs can be found in the appendix.

ii. Explanation of Logistic Regression

Logistic regression is used when the outcome variable is binary (e.g., bar exam pass/fail). Unlike the outputs from linear regression, the results from logit regressions are not directly interpretable. Logistic regression modeling produces outputs called "log odds," which provide insight on the relationship between variables that we analyze.

Log odds tell us two things: (1) general information about the impact of a change in the explanatory variable (or set of variables) on the outcome variable; and (2) whether those impacts are statistically significant. But log odds do not directly communicate, for example, the impact of a one-point increase in LSAT score on the likelihood of bar passage.

To increase the usefulness of the logistic regression outputs, we calculate the predicted probability of bar passage based on the amount of change of a given explanatory variable. Predicted probabilities are particularly useful because they help localize the impact of factors of interest by controlling for other potentially relevant factors.

C. Variables

i. Outcomes

We use two sets of primary outcomes: students' 1L LGPAs; and students' bar exam results and scores. Our analyses use the explanatory variables listed below to examine the extent to which they explain or predict a student's academic performance and bar passage (our "outcomes").

ii. Explanatory Variables

Our study utilizes several explanatory variables, depending on the outcome explored. We use:

- Students' highest LSAT score, final (cumulative) UGPA, and UGPA growth to explain and make predictions about LGPA.
- Students' 1L LGPA, LGPA growth, course credit hours, individual course LGPAs, LSAT score, and final UGPA to make predictions about their likelihood of bar passage.

Table 2 lists the explanatory and control variables considered in the analyses. Table 3 defines the specific coursework variables that were utilized.

In analyses that consider UGPA growth (the difference between a student's final and first-year UGPA), we take into consideration the student's starting place. Those students with higher first-year UGPAs have less opportunity to improve and, conversely, those with lower first-year UGPAs are less likely to worsen. Our models, therefore, include first-year UGPA in order for us to hold this variable constant. This means that when we report the results from these analyses, the effect of UGPA growth is based on a first-year UGPA held at the average (or other specified point) for all students.

Similarly, LGPA growth (the difference between a student's final and 1S LGPA) is considered alongside the student's starting place. Those students with higher 1S LGPAs have less opportunity to improve and, conversely, those with lower 1S LGPAs are less likely to decline. Our models include 1S LGPA, which allows us to examine the effect of LGPA growth while holding 1S LGPA constant.

TABLE 2

EXPLANATORY AND CONTROL VARIABLES USED IN THE ANALYSES

Variable Categorization	Variable Description(s)
Pre-Admission Factors	Encompasses variables which are typically reported or calculable based on the information reported in an applicant's CAS report: • First-year undergraduate GPA (UGPA) • Final UGPA • Highest LSAT score • UGPA growth – the difference between students' final UGPA and first year UGPA
Law School Performance Factors	Encompasses variables measuring students' academic performance in law school: • First-semester law school GPA (LGPA) • First-year LGPA • Final LGPA • LGPA growth – the difference between students' final LGPA and first semester LGPA • Course credit hours (doctrinal, clinic, or skills-based) • Individual course LGPAs (doctrinal, clinic, or skills-based)
Control Variables	Encompasses variables used as controls in the regression models for this report: • Race • Gender • Age at law school matriculation • First generation student status (yes/no) • Number of years to complete undergraduate degree • Selectivity of degree-granting undergraduate institution as measured by the acceptance rate • Whether the student was a transfer student (at undergraduate or law school level) • Law school class rank (for 1st, 2nd, and 3rd year) • Bar exam jurisdiction • Bar exam administration period

TABLE 3

COURSEWORK DESCRIPTIONS

	Description(s)
All Doctrinal Courses	Defined as any course that focuses on possible tested topics on the bar exam, regardless of whether it is required for graduation.
Upper-Level Doctrinal Courses	These are ONLY: • Criminal Procedure • Evidence • Conflict of Laws • Business Associations • Family Law • UCC Article 9 (Secured Transactions) • Trusts and Estates
Other Doctrinal Courses	These are any doctrinal courses not included in the above upper-level doctrinal courses category. The number of credit hours earned in this category is equal to the difference of credit hours earned in *All* Doctrinal Courses and the sum of the credit hours earned in *Upper-Level* Doctrinal Courses.
Other Coursework	We specifically investigate credit hours in: • Skill-based bar courses – courses in which the acquisition of skills that are relevant to the bar exam is the primary aim. The acquisition of content knowledge may occur in these courses, but skills training is the focus. (This category excludes legal writing courses, see below.) • Legal writing – courses that specifically focus on building legal writing skills in a practice setting (e.g., memorandum drafting, litigation drafting) rather than academic writing (e.g., seminars or law reviews). (Typically, these are considered "skill-based" courses, but we treat them separately in this study.) • Clinic-based – courses classified as legal clinics by the law school. • Externship – courses classified as externships or field placements by the law school. • Other electives – courses that are not accounted for in any of the above coursework definitions.

iii. Control Variables

As noted in each of the subsections in the Results Section, we consider a broad range of control variables—those that have a relationship with both the outcome and the explanatory variable. It is important to properly contextualize the role of these variables, particularly that of race/ethnicity in this study. Education researchers have repeatedly found important relationships between race/ethnicity and standardized test scores and other academic outcomes. It is necessary to include race/ethnicity whenever it is associated with both the outcome (e.g., bar exam result) *and* the predictor (e.g., LGPA) being studied. It is therefore important to consider how race/ethnicity alters the relationships between any of our outcomes or explanatory variables. In such a case, race/ethnicity is treated as a control variable and its only purpose is to “correct” the size of a predictive effect (for example, the predictive effect of LSAT score on 1L LGPA).

But these relationships should not be inferred to imply that any one racial/ethnic group is more or less likely to succeed in law school or the bar exam. As a concept, race/ethnicity itself is complex and should be treated as a proxy that captures those myriad life experiences (e.g., exposure to racism, family structure, parent education) that may be more common among individuals who identify similarly by race/ethnicity.

Considering our use of race/ethnicity as a control variable, we do not discuss any variations in our results across racial/ethnic groups. In addition, we omit race from all regression output tables. As a result, the relationships between race and any of the other variables are not deducible from any material in this report.

iv. Standard Deviations

Throughout this report, we frequently refer to increases and decreases in variables in terms of standard deviations. Describing relationships in these terms is a simple way to explain realistic changes between individuals. Nearly 70 percent of people will fall between one standard deviation below the mean and one standard deviation above the mean.

A standard deviation can be thought of as the average distance each individual person (or observation) is from the mean of a given variable (for example, highest LSAT score). The standard deviation is calculated by subtracting each person’s score on a given variable from the overall mean for that variable and squaring that number. These individual deviation scores are then added together and divided by the number of observations in your sample, minus 1. You then take the square root of this number to calculate the standard deviation.

5. APPENDIX

A. Summary Statistics

TABLE A.1

SUMMARY STATISTICS

	Obs.	Median	Mean	Standard Deviation	Minimum	Maximum
Preadmission Variables						
Highest LSAT Score	4,032	152	152.7	6.32	128	177
Final UGPA	3,987	3.30	3.27	0.46	1.73	4.31
First Year UGPA	473	3.25	3.19	0.62	0.44	4.17
UGPA Growth	472	0.04	0.06	0.50	-1.73	2.11
LGPA						
First Semester	4,025	2.92	2.90	0.56	0.95	4.22
First Year	4,000	2.93	2.91	0.52	1.33	4.21
Final	4,053	3.14	3.14	0.42	1.67	4.14
Growth	4,001	0.20	0.20	0.31	-0.80	2.62
Doctrinal LGPA						
Article 9	1,613	3.33	3.13	0.65	1.00	4.33
Business Associations	3,144	3.33	3.22	0.61	1.00	4.33
Conflict of Laws	582	3.33	3.21	0.61	0.70	4.33
Criminal Procedure	3,580	3.11	3.08	0.58	1.00	4.33
Evidence	3,753	3.00	3.06	0.70	1.00	4.33
Family Law	1,937	3.33	3.22	0.60	0.67	4.33
Trusts and Estates	2,750	3.00	2.97	0.65	1.00	4.33
Upper-Level Doctrinal Courses (Total)	1,447	3.42	3.38	0.39	2.05	4.21
Other Doctrinal Courses	2,545	3.00	3.00	0.47	1.55	4.19
All Doctrinal Courses	2,631	2.95	2.95	0.48	1.75	4.15
Credit Hours						
Clinic-Based	2,942	6	6.66	6.36	0	42
Externships	2,264	0	2.80	3.94	0	20
Legal Writing	792	7	5.53	3.23	1	16
Skills-Based	1,728	8	8.20	4.35	0	30
Upper-Level Doctrinal Courses	1,447	64	64.42	7.24	28	103
Other Doctrinal Courses	1,416	16	21.48	11.97	3	67
All Doctrinal Courses	2,863	49	44.20	12.03	3	86

Note: The values in this table are for the overall sample and may vary slightly from those described in the text. This is because we exclude participants who are missing values for key variables in each model. Students who did not graduate are included in this table, and therefore minimums of 0.00 earned credit hours are observed. Table 3 defines "upper-level", "other", and "all" doctrinal courses categories.

B. Regression Output Tables

TABLE A.2

WHAT PREDICTS LAW SCHOOL PERFORMANCE?
(PREDICTING 1L LGPA)

	Preadmission Factors	UGPA Growth
Highest LSAT Score	1.82 ***	
	(0.21)	
Final UGPA	0.65 ***	
	(0.10)	
UGPA Growth		1.97 ***
		(0.32)
First Year UGPA		1.80 ***
		(0.26)
Age	-0.01	
	(0.15)	
Selectivity of Undergraduate Institution	-0.10	
	(0.09)	
Gender: Male	-0.06	0.15 **
	(0.03)	(0.06)
R^2	0.14	0.10
Adj. R^2	0.13	0.10
Num. obs.	707	455

Note: * p < 0.05; All continuous variables are scaled 0-1. Race is included as a control variable, but those results are omitted from this table (see the Control Variables section above).

TABLE A.3

WHAT PREDICTS FIRST-TIME BAR PASSAGE?

	LSAT & UGPA	UGPA Growth	1L LGPA	LGPA Growth
Highest LSAT Score	5.95 ***			
	(0.51)			
Final UGPA	2.20 ***			
	(0.26)			
UGPA Growth		3.23 *		
		(1.38)		
First Year UGPA		2.17		
		(1.15)		
1L LGPA			6.96 ***	
			(0.32)	
LGPA Growth				10.05 ***
				(0.69)
1S LGPA				10.63 ***
				(0.46)
Age	-0.96 **	0.05	-1.73 ***	-1.77 ***
	(0.35)	(1.27)	(0.36)	(0.36)
Gender: Male			0.02	
			(0.09)	
AIC	3508.47	471.93	3090.76	2977.40
BIC	3593.15	508.79	3175.60	3062.24
Log Likelihood	-1740.23	-226.96	-1531.38	-1474.70
Deviance	3480.47	453.93	3062.76	2949.40
Num. obs.	3129	444	3165	3167

Note: * $p < 0.05$; All continuous variables are scaled 0-1. Race is included as a control variable, but those results are omitted from this table (see the Control Variables section above).

TABLE A.4

WHAT PREDICTS FIRST-TIME BAR PASSAGE?
(COURSE LGPA MODELS)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Doctrinal (Overall	8.34 *** (0.41)									
Upper-Level Doctrinal		9.27 *** (1.03)								
Other Doctrinal			7.05 *** (0.38)							
Article 9 LGPA				4.63 *** (0.38)						
Business Associations LGPA					4.76 *** (0.27)					
Conflict of Laws LGPA						4.07 *** (0.65)				
Criminal Procedure LGPA							5.47 *** (0.27)			
Evidence LGPA								5.11 *** (0.23)		
Family Law LGPA									4.36 *** (0.35)	
Trusts and Estates LGPA										4.44 *** (0.26)
AIC	1779.07	320.85	1972.29	1316.02	2862.20	525.84	3353.01	3319.11	1930.84	2876.83
BIC	1790.42	330.05	1983.63	1326.44	2874.06	534.45	3365.15	3331.33	1941.75	2888.51
Log Likelihood	-887.53	-158.43	-984.15	-656.01	-1429.10	-260.92	-1674.51	-1657.55	-963.42	-1436.42
Deviance	1775.07	316.85	1968.29	1312.02	2858.20	521.84	3349.01	3315.11	1926.84	2872.83
Num. obs.	2154	735	2139	1349	2787	547	3188	3324	1727	2539

Note: * $p < 0.05$; All continuous variables are scaled 0-1. Race is included as a control variable, but those results are omitted from this table (see the Control Variables section above). Table 3 defines "upper-level", "other", and "all" doctrinal courses categories.

TABLE A.5
WHAT PREDICTS FIRST-TIME BAR PASSAGE?
(COURSE CREDIT HOURS MODELS)

	Model 1	Model 2	Model 3	Model 4	Model 5
Doctrinal (Overall)	2.03 ***				
	(0.29)				
Upper-Level Doctrinal					1.44 *
					(0.71)
Other Doctrinal		1.34 ***			
		(0.34)			
Clinic-Based			5.93 **		
			(2.12)		
Externship			-1.18		
			(0.65)		
Legal Writing			0.33		
			(0.70)		
Skills-Based				-0.81 *	
				(0.41)	
1L LGPA	7.84 ***	7.50 ***	7.95 ***	8.60 ***	9.11 ***
	(0.33)	(0.43)	(0.80)	(0.48)	(0.55)
AIC	3248.21	1843.15	464.95	1692.79	1379.59
BIC	3309.21	1898.35	512.03	1747.34	1432.36
Log Likelihood	-1614.10	-911.57	-221.47	-836.40	-679.79
Deviance	3228.21	1823.15	442.95	1672.79	1359.59
Num. obs.	3297	1844	534	1728	1447

Note: * $p < 0.05$; All continuous variables are scaled 0-1. Race is included as a control variable, but those results are omitted from this table (see the Control Variables section above). Table 3 defines "upper-level", "other", and "all" doctrinal courses categories.

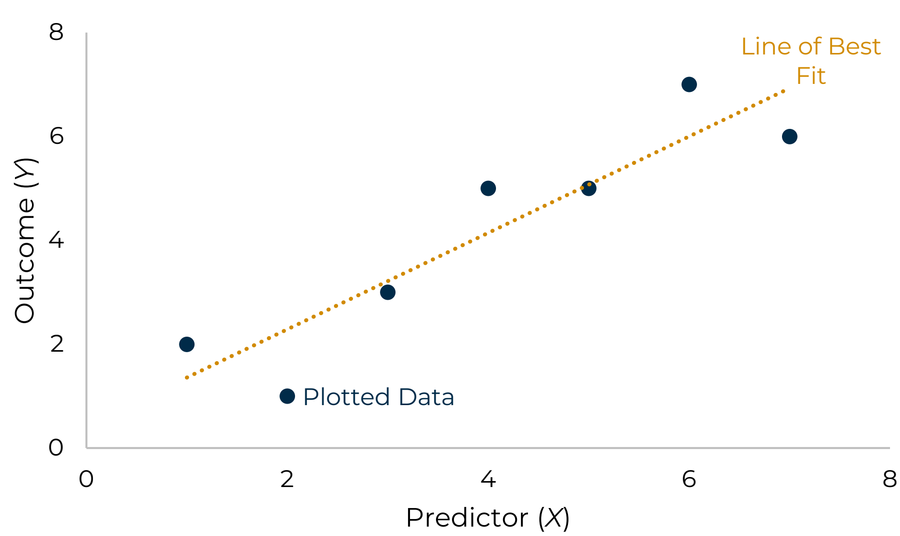
C. Interpreting Linear Regression

Ordinary least squares (OLS) regression, often referred to simply as "linear regression," estimates the relationship between at least one independent variable (predictor) and one dependent variable (outcome), the latter being distributed continuously (i.e., taking on any value, including negative values) or, in many cases, discretely (i.e., taking on only a finite number of values). As noted above (see p. 21), the outcomes 1S LGPA, 1L LGPA, final LGPA, final UGPA, and UGPA growth are classified as discrete variables because they can take on a value only within a finite set of options. There are, however, enough possible values of these particular variables that OLS regression is appropriate.

In addition to independent and dependent variables (predictors and outcomes), linear regression models often incorporate control variables—variables that have statistical relationships with the dependent *and* independent variable. Examples of control variables include race, gender, and age.

Linear regression uses independent, dependent, and control variables to map a line of best fit to a dataset. As an example, imagine a scatterplot where an independent variable, *x* is represented along the horizontal axis, and the dependent variable, *y is* represented along the vertical axis. Linear regression estimates the effect of *x* on *y* by drawing a line through the data that minimizes the distance between the line and the plotted data points. This concept can be extended to incorporate the effects of multiple independent and control variables on the outcome variable *y*.

FIGURE A.1
Linear Regression Estimates a Line of Best Fit



The output of a regression model includes a coefficient for each independent and control variable (note: the coefficients of control variables should NOT be interpreted, and conclusions should NOT be drawn from the coefficients obtained by them—they may be loosely informative, but they are generally not inferentially useful). It is important to note three pieces of information conveyed by each coefficient: direction, size, and statistical significance. All three of these factors should be taken into consideration when determining whether a result is meaningful.

Direction. The sign (positive or negative) indicates the direction of the effect. A positive result (the default is to denote this with no "+" sign) means that a positive change in *x* is associated with a positive change in *y* or that a negative change in *x* is associated with a negative change in *y*.

Size. The actual value of the coefficient denotes the size of the effect that a predictor variable has on the dependent variable. The further the number is from zero, the stronger the relationship is. Often size is interpreted as the effect on *y* of a one-unit change in *x* (for example, increasing LSAT score from 141 to 142 or UGPA from 3.2 to 4.2).

Statistical Significance. Whether the coefficient is labeled with an asterisk (or asterisks) indicates statistical significance. This is a commonly used criterion to determine whether the result is "trustworthy" or might be due to chance alone. It is important to note that statistical significance test *only* captures confidence that the result is NOT zero. Thus, statistical significance cannot and does not indicate whether the result has any meaningful application. In other words, a result can be practically important even when it is not statistically significant.

Comparing the size of effects in cases where more than one predictor variable is used, as is the case in multivariate regression and in the results presented in this report, is often difficult when those variables have very different ranges. As with the LSAT score and UGPA example above, a one-unit change in LSAT is appreciably different than a one-unit change in UGPA. To better compare their effect on the outcome, it is useful to rescale the predictors. This can be done in many ways, but for the purposes of this report, these variables were rescaled to range 0 to 1.

In this case, 0 represents the minimum value of the variable and 1 the maximum value. Thus, when the size of the coefficient is discussed, we discuss how a change from the minimum to the maximum affects the outcome. Since these variables are both measured on the same scale, the coefficients can be more easily compared to determine which has a stronger relationship with the outcome.

One important measure of the quality of a linear regression model is R^2, which expresses the percentage of the variation in the data that the linear regression model explains. As a percentage, the values range from 0 to 1, with a higher R^2 indicating that the model better explains the outcome. For example, a R^2 value of .42 would mean that the model explains 42 percent of the variation in the outcome.

Interpreting R^2 should be done with some caution because adding any variable, regardless of its relationship with the outcome (even if totally unrelated), to a model will always increase R^2. It is, therefore, possible that the reported R^2 is too high, perhaps as a result of the researcher attempting to increase the visibility and attention of their findings. More likely, however, is the threat that the model may be overfitted.

An overfitted model is one that explains so well the particularities of the specific data that the researcher is using that it cannot be generalized to other samples or to the population. This is often a concern in cases when R^2 approaches 1, for example when it exceeds 0.8.

Often, the adjusted-R^2 is used to protect against overfitting by estimating whether the addition of a particular variable better improves the explanatory ability of the model. It does so by adding a penalty to each independent variable in the model. In general, a variable is omitted from the model if its addition does not increase the adjusted-R^2.

D. Interpreting Logistic Regression

Logistic regression estimates the relationship between at least one independent variable (predictor) and one categorical dependent variable (outcome), the latter being a variable with a limited number of possible values. For these analyses, we focus exclusively on a specific form of logistic regression where the outcome is binary/dichotomous (that is, it can only take on one of two possible values). The relevant variable of interest in this report is bar exam result; whether a graduate passed or failed the bar exam.

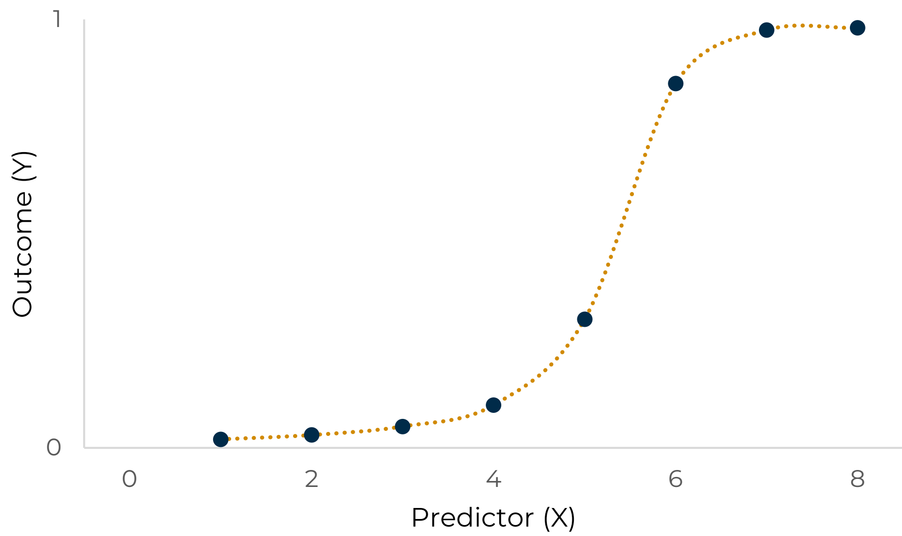
In addition to independent and dependent variables (predictors and outcomes), logistic regression models often incorporate control variables—variables that have statistical relationships with the dependent *and* independent variables. Examples of control variables include race, gender, and age.

Logistic regression uses these independent, dependent, and control variables to map a s-curve of a dataset. As an example, imagine a scatterplot where an independent variable, *x* is represented along the horizontal axis, and the dependent variable, *y is* represented along the vertical axis. Logistic regression estimates the effect of *x* on *y* by drawing a curve between a 0-1 value on the vertical axis. The shape of the curve stems from the fact that the outcome cannot be less than 0 or greater than 1, and thus the curve plateaus as values approach either 0 or 1 one on the y axis.

This concept can be extended to incorporate the effects of multiple independent and control variables on the outcome variable, *y*.

FIGURE A.2

LOGISTIC REGRESSION FITS AN S-SHAPED (SIGMOIDAL) LINE



Like the output of a linear regression model, a logistic regression's outputs include a coefficient for each independent and control variable and it is important to note the coefficient's direction, size, and statistical significance whenever making a determination as to whether the effect is practically significant (see Appendix 1 above).

Unlike linear regression, the coefficients attained from logistic regression cannot be interpreted directly. Logistic regression performs a transformation of the outcome variable. The result of this transformation is that the interpretation of the coefficient becomes: a one-unit change in the independent variable is associated with a x change in the log-odds of the outcome variable.

Predicted probabilities are generated by entering values into the right-hand side of the model and performing the necessary math to get the corresponding outcome value.

The estimation method used in logistic regression differs from OLS regression, which means that the R^2 statistic is not applicable. Several useful measures are available to test how well the model predicts the outcome, but none used here report the percent of variation in the outcome that is accounted for by the variables in the model. In this report, we use what is referred to as a "pseudo-R^2," which is a relative measure of model fit and is used to compare to other pseudo-R^2 values obtained from similar models estimating the same outcome. When comparing two values, the larger value indicates a better fit.

E. Statistical Significance

Quantitative models produce information on whether a given variable is *statistically significant*.

TABLE A

SAMPLE MODEL RESULTS

	Dependent variable:	
	Final LGPA	
	(1)	(2)
LSAT Score	0.028**	0.026**
	(< 0.01)	(< 0.01)
Undergraduate GPA		1.285*
		(<0.05)
Gender (female)	-0.012**	-0.046
	(< 0.01)	(0.221)
Constant	-19.694**	-24.023**
	(< 0.01)	(< 0.01)
Observations	658	654
Log Likelihood	-294.423	-281.326
Akaike Inf. Crit.	594.847	570.651

Note: $^{*}p<.05$, $^{**}p<0.01$

In the sample table to the right, two slightly different models predicting LGPA are shown. For each variable's coefficient, one or two asterisks indicates statistical significance, while having no asterisks indicates a lack of statistical significance.

If a variable is statistically significant, we can say with confidence that its estimated effect (denoted by the value of the coefficient) is "real", or different from zero. There is always some chance that model estimates are the product of randomness in the data; statistical significance means that the associated variable's effect on the dependent variable—bar passage, in this example—is likely to be a genuine effect and not the product of random chance.

Statistical significance is a distinct concept from *substantive significance*. Statistical significance is only concerned with the likelihood that a coefficient estimate is a genuine one; it does not speak to the size of the impact that the variable has on the outcome. For example, *gender* in Model 1 above is statistically significant, but the value of the coefficient is quite small. While the model does find a statistical difference with respect to gender and bar passage, when the odds of bar passage are calculated according to the value of this coefficient, the change is quite small and is not substantively significant.

Unlike statistical significance, there is no clear threshold for what is and is not *substantively* significant. In light of this, we routinely report the interpretation of each finding and discuss whether it has, or is likely to be considered to have, a substantive impact on academic performance—but we do not offer a strict categorization of whether each predictor is substantively significant. For example, we may report that some change in a predictor increases academic performance by 0.01 points on LGPA, and we may mention in discussion that this change is small, but it is not inherently considered substantively insignificant.

We discuss results considering both statistical and substantive significance. We highlight results that are statistically significant but may not discuss them at length if they are substantively insignificant. Similarly, we may discuss coefficients that have a large impact on academic performance even if they are not statistically significant.

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