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Ruth Bader Ginsburg SCHOOL OF LAW

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BAR EXAM SUCCESS ANALYSES

FINAL REPORT FOR RUTH BADER GINSBURG SCHOOL OF LAW

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NOVEMBER 2022

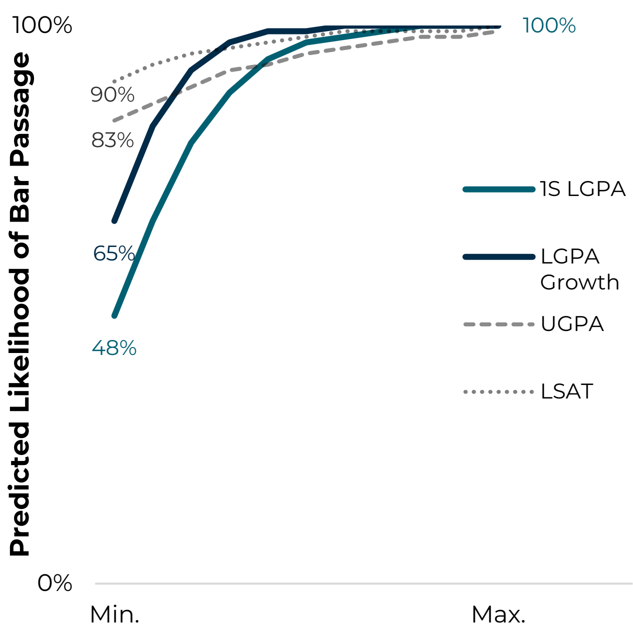
MOTIVATION

This report provides the information you need to understand how admissions factors (such as undergraduate GPA [UGPA], LSAT scores, and UGPA Growth) and law school GPA (LGPA) relate to first-time and ultimate bar passage. Understanding the relationships between these variables provides valuable insight into the ways in which students learn, the challenges they face, and the interventions that can potentially help them to overcome those challenges.

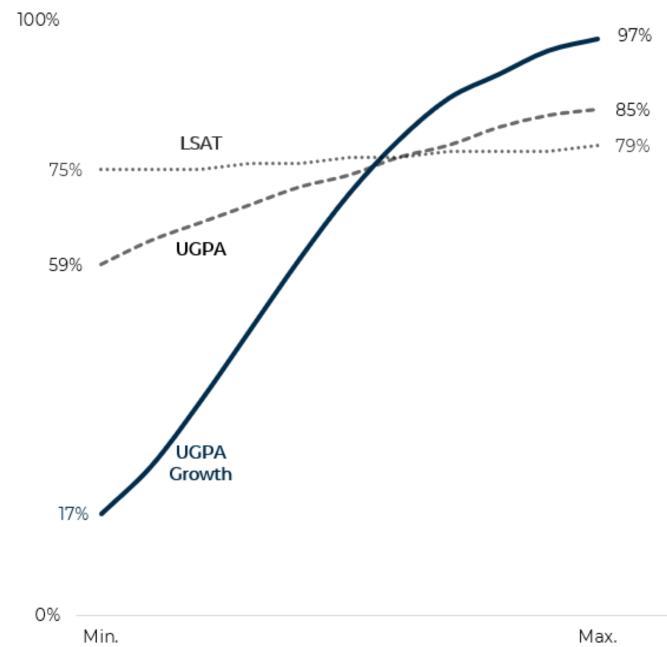
KEY FINDINGS

- LSAT and UGPA have only limited predictive ability regarding early LGPA and bar passage.
- LGPA growth and all LGPA variables better predict first-time and ultimate bar success than LSAT score and final UGPA.
- UGPA growth is the most influential preadmission factor in predicting LGPA and bar passage.

LGPA Variables Have Larger Effects on Predicted Bar Passage Than Highest LSAT Score or Final UGPA



UGPA Growth Predicts First-Time Bar Passage as Well as or Better Than Highest LSAT Score and UGPA



The figure above shows that UGPA growth predicts first-time bar passage better than LSAT score or final UGPA. The steepness of the slope of UGPA growth (the bolded blue line) is markedly steeper than the slope of either LSAT or UGPA. In relative terms, the effect of UGPA growth is slightly larger than that of LSAT score and about 35 percent larger than final UGPA.

RECOMMENDATIONS

- Continue to track LGPA across each year of law school to target interventions toward students with lower likelihood of first-time bar passage.
- When prioritizing equity in the admission process, consider placing greater weight on UGPA growth than LSAT score or final UGPA alone.
- Place more emphasis on LGPA than LSAT score or UGPA when estimating the likelihood of bar passage.

CONTENTS

A. 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 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 law school GPA (LGPA), coursework, and preadmission factors. We also explore the extent to which preadmission factors, namely LSAT score and undergraduate GPA (UGPA), 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.

1. Data and Demographic Statistics

Ruth Bader Ginsburg Law submitted deidentified demographic and academic data for students who matriculated in 2012 through 2016. These data were used to prepare this report.

Of the 1356 individuals comprising the sample, 0 attritted, 19 transferred in, and none transferred to another school (see Table 1 on next page).

TABLE 1
Sample Demographic Characteristics

	2012-2016 Entering Cohorts	
	Count	**Percent[1]**
Gender		
Female	627	46
Male	729	54
Race/Ethnicity		
Black	54	4
White	1100	81
Remaining	202	15
Enrollment		
Transfer in	19	1
Transfer out	0	0
Attrition	0	0
Avg. years to graduate	3	–
Undergraduate Institution Ranking[2]		
Top 50	60	4
51-100	404	30
101+	114	8
Undergraduate Major		
Business	182	13
Criminal Justice	49	4
Humanities	112	8
Political science and law	273	20
Social science (other)	148	11
Other	582	43
Total	1356	–

Notes: [1]Totals may not add to 100 due to rounding. [2] *2022 College Rankings and Lists*, U.S. NEWS & WORLD REP., https://www.usnews.com/best-colleges/rankings.

2. Analytical Approach

As noted above, this report aims to identify predictors of bar passage and law school GPA (LGPA). Predictors of each are summarized separately in the results that follow.

For the analyses of bar passage (pass or fail), we construct logistic regression models and examine the extent to which LGPA, LSAT score, final UGPA, and UGPA growth predict first-time and ultimate passage. We report the results as changes to a student's predicted probability of passing the bar exam. We also utilize ordinary least squares

(OLS) linear regression models to explore the relationships between a student's first bar exam score and their LGPA, LSAT score, and UGPA. We report the results of these linear regressions as increases or decreases in bar score.

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

B. RESULTS

1. What Predicts Bar Exam Passage and Performance?

We first investigate determinants of bar passage by examining the relationships between the outcome variables (first-time and ultimate bar passage [pass/fail], and first-time bar exam score) and several other factors. We begin with a look at the relationships between bar passage and LGPA. These analyses account for other factors that could have an impact on both LGPA or bar passage, so the results that follow hold true even when other student characteristics, such as matriculation year and race/ethnicity, vary.

a. LGPA

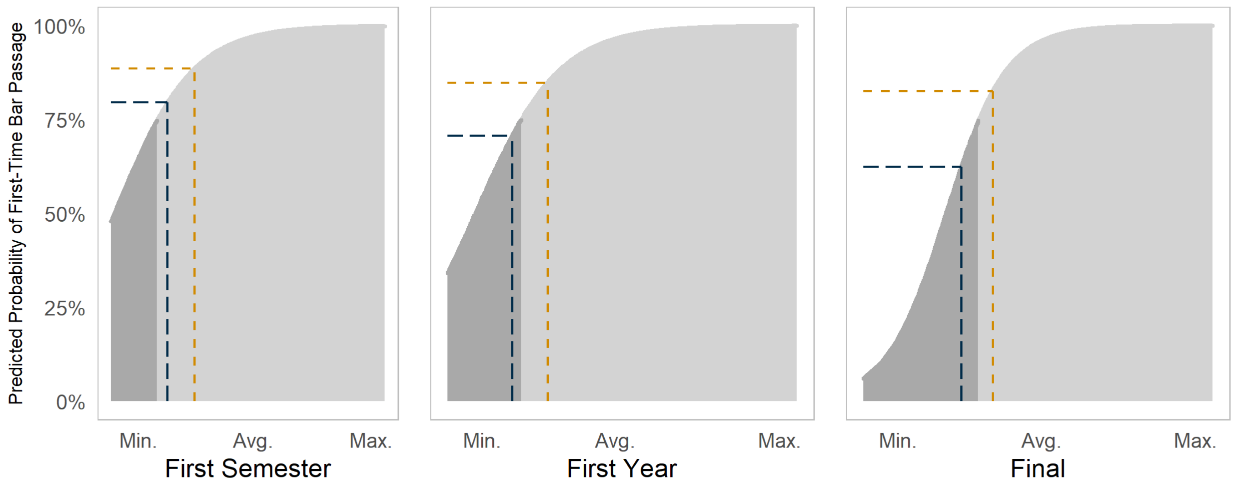
An increase in each LGPA (first-semester [1S], first-year [1L], and final) is associated with an increased, statistically significant predicted probability of passing the bar exam on the first attempt. Figure 1 shows the predicted likelihood of first-time bar passage for various levels of 1S (left figure), 1L (center figure), and final (right figure) LGPA. The blue dashed line represents the fifth percentile of the given LGPA predictor, and the yellow dashed line represents the value one-half-standard-deviation above the fifth percentile. The dark gray area under the curve represents those LGPAs which are associated with less than a 75 percent predicted probability of first-attempt bar exam passage:

- 1S LGPA below 2.31.
- 1L LGPA below 2.42.
- Final LGPA below 2.75.

This final LGPA threshold might be a helpful goal for which students should strive and for academic support faculty and staff to use as a benchmark. Tracking whether a student is on pace to meet or exceed the 2.75 final LGPA might be a helpful monitoring effort (see Figure 1 on next page).

FIGURE 1

The Predicted Probability of First-Time Bar Passage Increases as LGPA Increases, With the Largest Benefit for Those With LGPAs Below 2.90–3.01 Grade Points



The effect of LGPA is largest for those students in the dark gray area, where the lines' slopes are steepest. Within these areas, an increase in LGPA (even a modest one) is associated with marked increases in predicted probability of first-time bar passage. Beyond these areas, the curves of the lines begin 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 in the dark gray areas 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.

To demonstrate the importance of LGPA within these ranges, on each plot in Figure 1, we indicate the differences in predicted probability of first-time bar passage for two different students. The blue dashed line represents a student with an LGPA at the fifth percentile and the yellow dashed line represents a student with an LGPA one-half a standard deviation above it. The space between where the two lines meet the y-axis is the increase in predicted probability of first-time bar passage.

An increase in:

- **1S LGPA** from 2.38 grade points (the fifth percentile) by 0.20 (one-half a standard deviation) to 3.08 is associated with a **9-percentage-point increase** in the predicted likelihood of first-time bar exam passage.

- **1L LGPA** from 2.37 grade points (the fifth percentile) by 0.21 grade points (one-half a standard deviation) is associated with a **14-percentage-point increase** in the predicted likelihood of first-time bar exam passage.

- **Final LGPA** from 2.66 grade points (the fifth percentile quartile) by 0.17 grade points (one-half a standard deviation) is associated with a **20-percentage-point increase** in the predicted likelihood of first-time bar exam passage.

As with first-time bar passage, *higher 1S and 1L LGPAs are associated with greater, statistically significant predicted probabilities of passing the bar exam within their first three attempts* (noted hereafter as "ultimate bar passage"). The benefit of increasing LGPA tends to wane once 1S and 1L LGPA reach about 2.67 grade points. Beyond these levels, graduates have more than an 85 percent chance of ultimately passing the bar exam. (See Appendix, Figure A.3.)

b. LGPA Growth

In addition to analyzing point-in-time LGPA measures, we examine the extent to which LGPA growth—the difference between a student's first-semester and final LGPA—is associated with the likelihood of bar passage.

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 2

LGPA Growth Among Students With Average and Below Average 1S LGPAs is Associated With Markedly Greater Predicted Probability of Bar Passage

Above Average, Average, and Below Average 1S LGPA

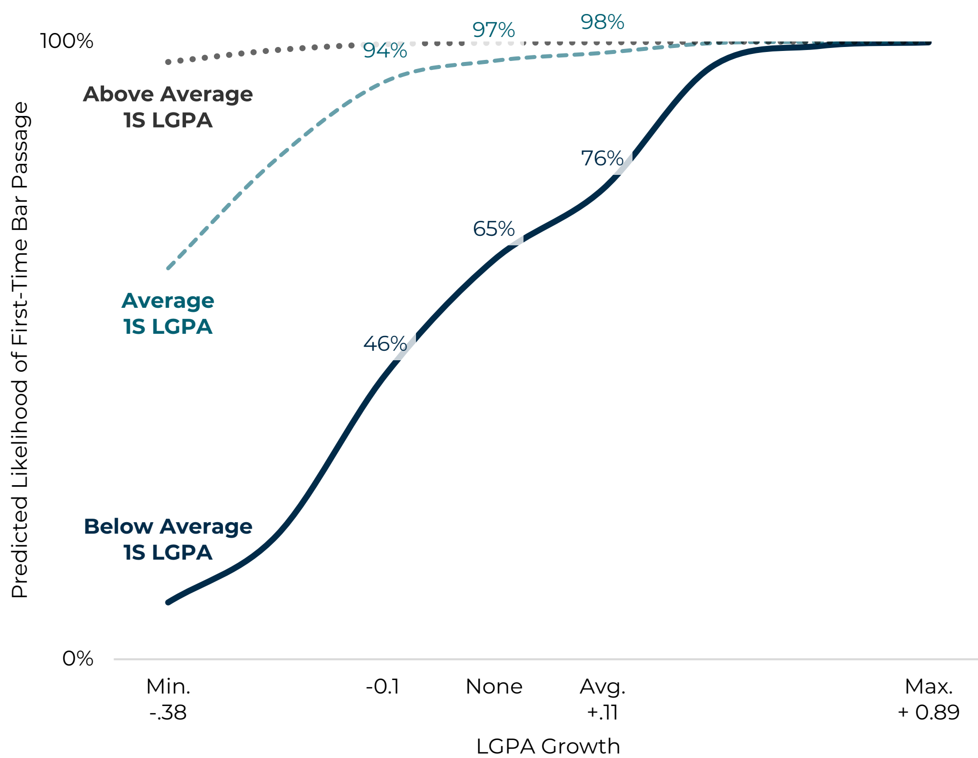


Figure 2 (above) shows how a student's predicted probability of first-time bar passage changes based on their LGPA growth. The blue line represents a student with below average 1S LGPA, the dashed teal line represents a student with average 1S LGPA, and the gray dotted line represents a student with above average 1S LGPA. Regardless of 1S LGPA, the influence of LGPA growth is noteworthy, particularly for those with average 1S LGPAs.

Holding all else constant, on average, a student with a below-average 1S LGPA that increases their LGPA from the first semester to graduation (moves to the right along the x-axis) by just 0.11 grade points (the average for RBG Law students) has a predicted probability of first-time bar passage 11 percentage points greater than a student with no growth and 30 percentage points greater than a student whose LGPA declines by 0.1 grade points.

The influence of LGPA growth is also notable among students with average 1S LGPAs (dashed teal line), although larger increases in LGPA are needed to realize more sizable increases in predicted probability of first-time bar passage. Among these students, one who improves their LGPA by 0.1 grade points from their first semester to graduation is predicted to have a probability of first-time passage 2 percentage points higher than a student whose LGPA did not grow and 4 percentage points greater than a student whose LGPA diminished by 0.1 grade points.

LGPA growth is most important in the first year of law school, with diminishing returns after Year 1. Students face an uphill battle to improve their cumulative LGPAs as more grades are recorded. As such, although opportunity certainly remains to encourage improvement after the 1L year, encouraging and supporting students who struggle early on can help motivate them to maximize their opportunity to persevere and improve.

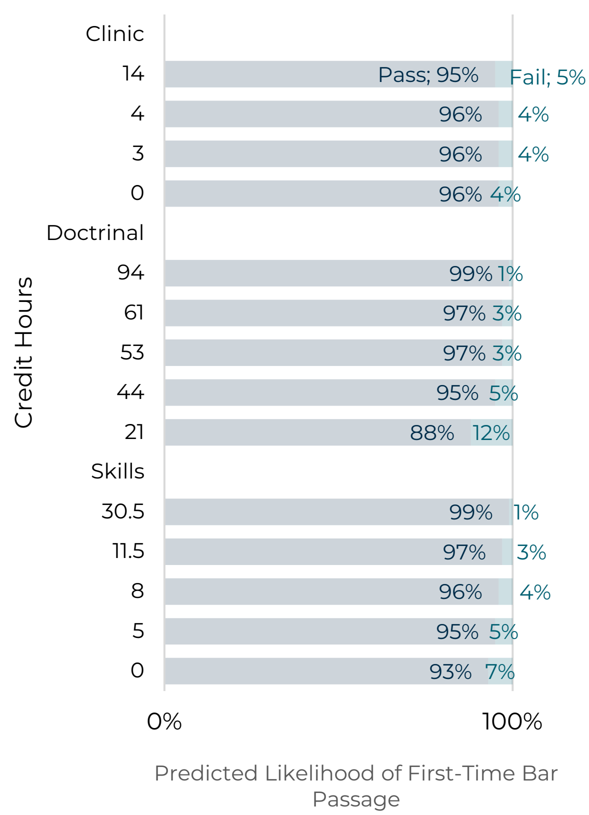
c. Clinic, Doctrinal, and Skills-Based Credit Hours

In this section, we examine the effect of clinic, doctrinal (i.e., rule-based and often bar-tested law) and skill-based credit hours on a student's predicted likelihood of passing the bar exam on their first attempt.

Figure 3 shows the predicted probabilities of first-time bar passage by the number of credit hours in clinic, doctrinal, and skill-based courses. In this model, we include students' 1L rank because there is a strong relationship between student academic performance and enrollment in these courses. Including 1L rank allows us to control for what is called *selection bias*, which results when enrollment in a course is due to a factor that is also related to the outcome. In this case, student rank predicts the number of credit hours in clinic, doctrinal, and skill-based courses *and* first-time bar passage.

FIGURE 3

The Predicted Probability of Passing the Bar (in Blue) Increases as Doctrinal Credit Hours and Skills Credit Hours Increase and When Enrolled in a Skills Course



Accounting for a student's 1L rank, we find that the predicted probability of first-time bar passage:

- Remains largely unchanged as the number of clinic credit hours increases. Students with the highest number of clinic credit hours have a predicted likelihood of first-time bar passage only 1 percentage point below those with no clinic credit hours.
- Increases as the number of credit hours in doctrinal courses increases. Students who take more than the minimum 21 credit hours have greater predicted probabilities of first-time bar passage: an increase from the minimum credit hours (21) to the maximum (94) is associated with a 11-percentage-point increase in predicted probability of first-time bar passage.
- Increases as the number of credit hours in skill-based courses increases. Students who take a skills course have greater predicted probabilities of first-time bar passage: compared to taking no skills courses, taking the maximum 30.5 credits of skills courses is associated with a 6-percentage-point increase in predicted probability of bar passage.

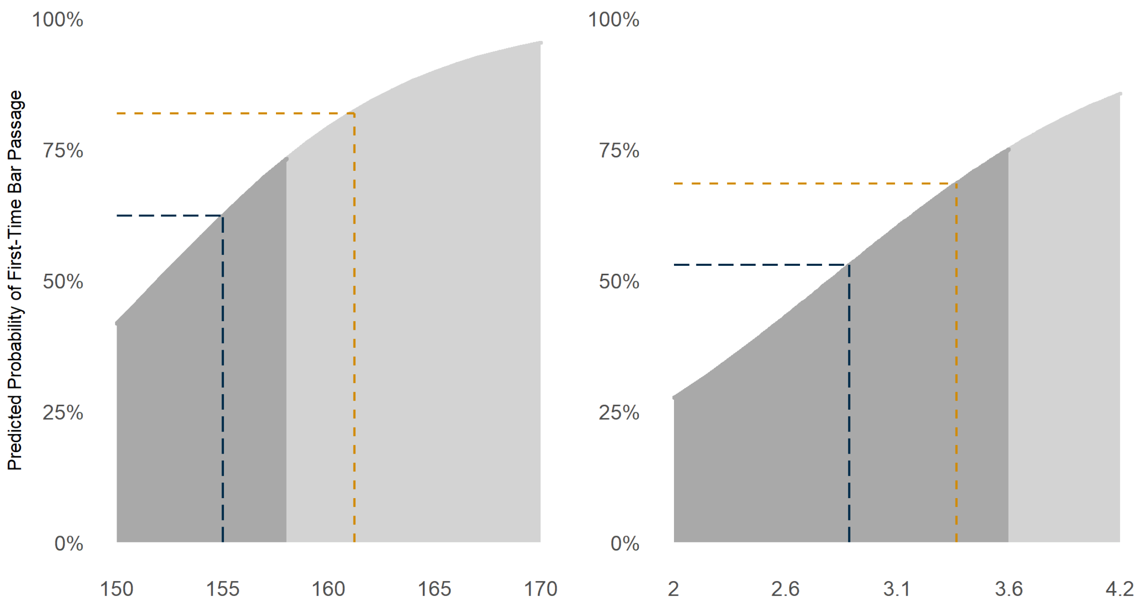
d. Undergraduate Admissions Factors

Below, we examine the extent to which LSAT score and UGPA predict first-time bar passage. We then contextualize the size of these effects by comparing them with those achieved when using LGPA to predict bar passage.

In Figure 4 (as with Figure 1), 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 bottom quartile and the yellow dashed line represents a student one standard deviation above. 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 4, the effects of LSAT score and UGPA are largest for students with a highest LSAT score and final UGPA below 152 and 3.59 grade points, respectively.

FIGURE 4

Predicted Probability of First-Time Bar Passage Increases as UGPA and Highest LSAT Score Increase



We find that *both LSAT score and UGPA are statistically significantly related to bar passage; however, these relationships are quite modest.*

An increase in highest LSAT score from 153 (the bottom quartile) by:

- **One point** is associated with a **1-percentage-point increase** in predicted probability of bar passage.
- **Five points** (one standard deviation) is associated with a **1-percentage-point increase** in predicted probability of bar passage.
- **Twenty-seven points** (up to the maximum 170) is associated with a **10-percentage-point increase** in predicted probability of bar passage.

An increase in final UGPA from 2.83 (the bottom quartile) by:

- **One-tenth of a point** is associated with a **1-percentage-point increase** in predicted probability of bar passage.
- **Four-tenths of a point** (one standard deviation) is associated with a **12-percentage-point increase** in predicted probability of bar passage.
- **More than one grade point** (up to the maximum 4.15) is associated with a **45-percentage-point increase** in predicted probability of bar passage.

Overall, as shown by the steepness of the lines' slopes in Figure 5, *each LGPA variable, including LGPA growth, has a greater measurable influence on bar passage than LSAT score or final UGPA.* (Although Figure 5 does not include 1L LGPA and final LGPA, the lines for these LGPAs closely match that of 1S LGPA.)

The size of the predictive effects[1] of:

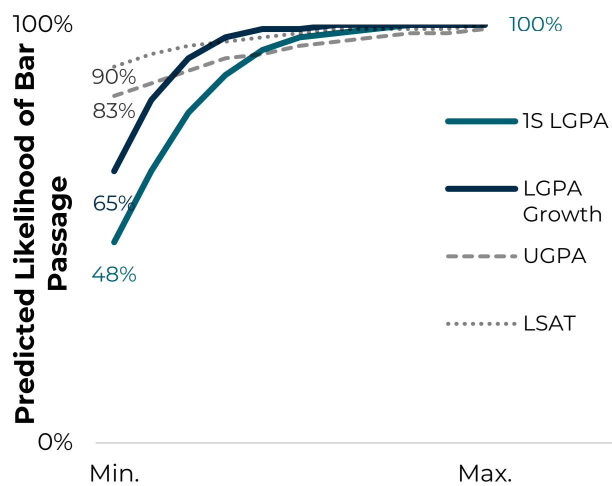
- 1S LGPA and 1L LGPAs are more than twice as large as those of LSAT score and final UGPA.
- Final LGPA and LGPA growth are more than two-and-a-half times larger than that of LSAT score and over three times that of final UGPA.

This suggests that LGPA is a stronger predictor of first-time bar passage and therefore could be leveraged to identify at-risk students and target them for intervention.

FIGURE 5

LGPA Variables Have Larger Effects on Predicted Bar Passage Than Highest LSAT Score or UGPA

X-axis labels represent minimum and maximum value of UGPA, LSAT, 1S LGPA, or LGPA Growth



e. 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. As we do with LGPA growth, we account for the student's starting place in these analyses.

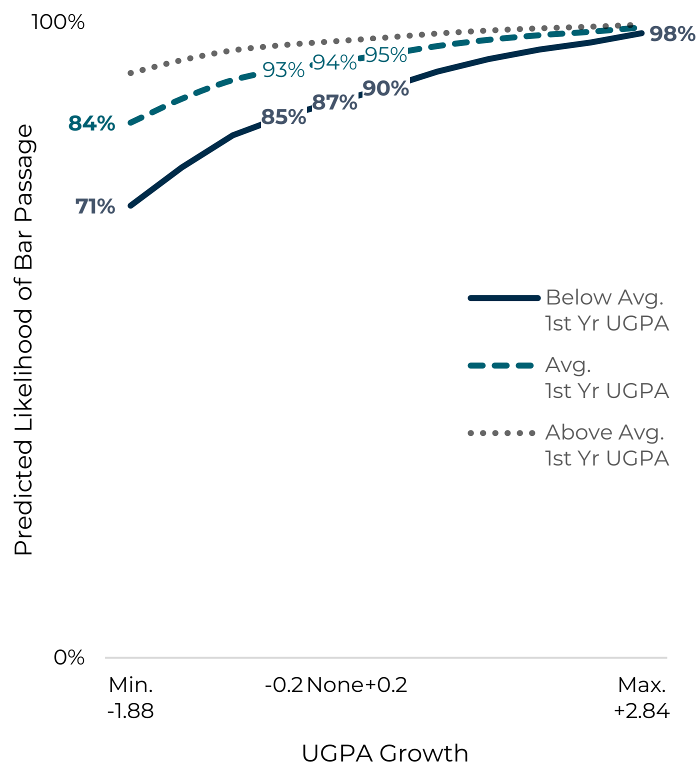
We find that *as UGPA growth increases, so too does the predicted probability of first-time bar passage*. For negative UGPA growth, the predicted probability of passage decreases.

[1] The size of the predictive effect refers to the size of the increase in predicted bar passage when the independent variable (e.g., 1S LGPA) increases (e.g., from the minimum to the maximum).
[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.

As with Figure 2, Figure 6 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 0.2 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 5 percentage points greater than a student whose UGPA diminished by 0.2 grade points.

FIGURE 6

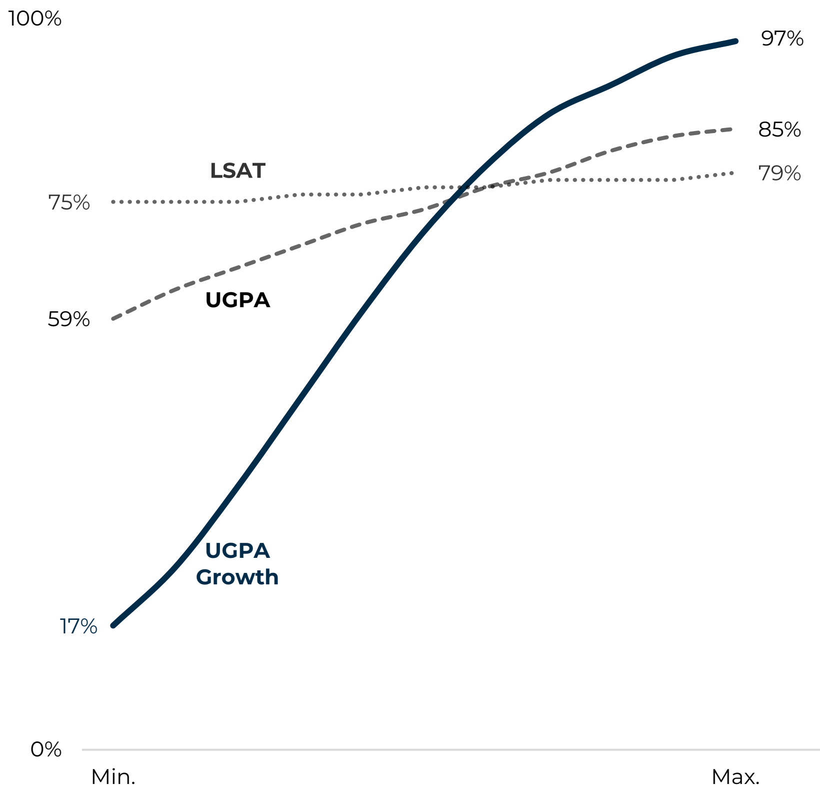
Positive UGPA Growth Is Associated with Increased Predicted Probability of First-Time Bar Passage, Irrespective of Starting UGPA



Furthermore, we find that *UGPA growth predicts first-time bar passage better than LSAT score or final UGPA*. As shown in Figure 7, the steepness of the slope of UGPA growth (the blue line) is markedly steeper than the slope of either LSAT or UGPA. In relative terms, the effect of UGPA growth is slightly larger than that of LSAT score and about 35 percent larger than final UGPA.

FIGURE 7

UGPA Growth Predicts First-Time Bar Passage as Well as or Better Than Highest LSAT Score and UGPA



2. What Predicts Law School Performance?

We next investigate determinants of academic performance by examining the relationships between the outcome variables (1S, 1L, and final LGPA) and preadmission factors that are available at the time of application to law school: students' LSAT score and UGPA. As with our examination of bar exam performance, these analyses account for several additional factors that could have an impact on both LGPA and the predictor variables, so the results that follow hold true even when other student characteristics, such as matriculation year and race/ethnicity, vary.

a. LSAT Score and UGPA

Top LSAT score and UGPA are statistically significantly related to 1S and 1L LGPA; however, they have limited utility when it comes to predicting LGPA.

An increase in highest LSAT score of:

- **One point** is associated with a **0.02-point increase** in both 1S LGPA and 1L LGPA and a **0.01-point increase in final LGPA**.
- **Five points** (one standard deviation) is associated with a **0.14-point increase** in both 1S LGPA and 1L LGPA and a **0.1-point increase in final LGPA**.
- **Twenty points** (the difference between the minimum 150 and maximum 170 score) is associated with a **0.48-point increase in 1S LGPA**, a **0.49-point increase in 1L LGPA**, and a **0.38-point increase in final LGPA**.

An increase in final UGPA of:

- **One-tenth of a point** is associated with a **0.01-point increase in 1S LGPA, 1L LGPA, and final LGPA**.
- **Three-sixths of a point** (one standard deviation) is associated with a **0.09-point increase in 1S LGPA, a 0.10-point difference in 1L LGPA**, and a **0.12-point increase in final LGPA**.
- **More than two grade points** (the difference between the minimum 1.86 and the maximum 4.04) is associated with a **0.21-point increase in 1S LGPA**, a **0.23-point increase in 1L LGPA**, and a **0.36-point increase in final LGPA**.

By the end of law school, LSAT score and UGPA explain only 27 percent of the variation in final LGPA. This suggests that nearly three-quarters (73 percent) of what *does* explain a student's academic performance may be attributable to what happens after students enter law school.

b. UGPA Growth

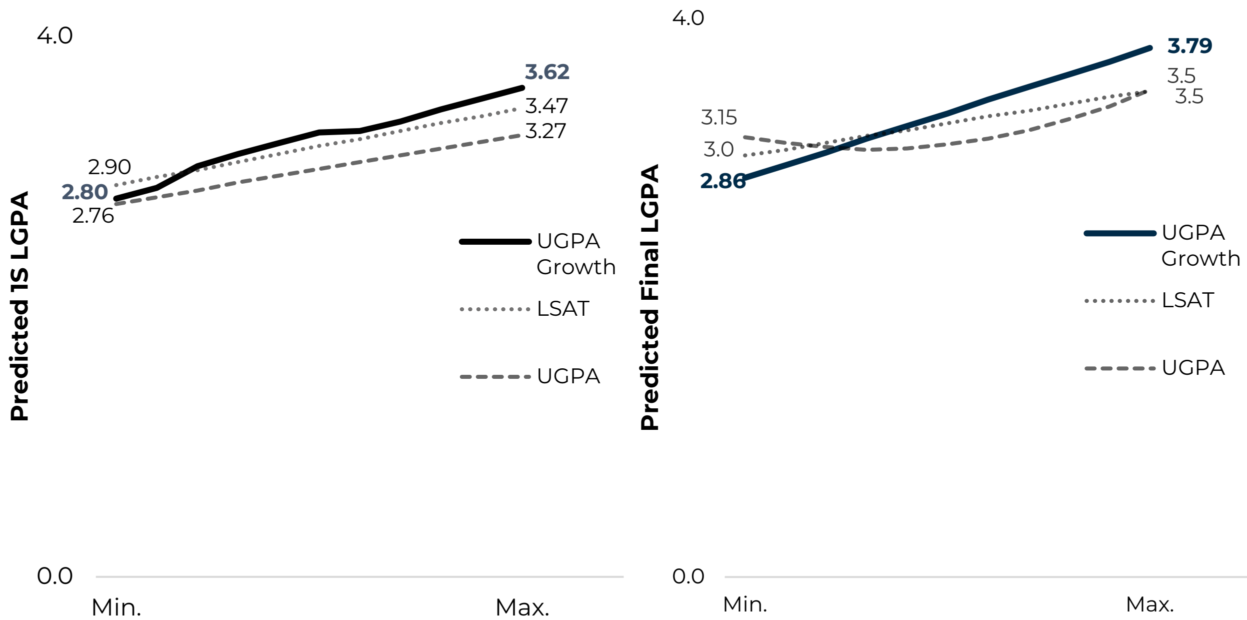
We also consider other transcript data that could help identify students with greater propensity for early academic success in law school. To do this, we add the following variables to the models (continuing to use 1S, 1L, and final LGPA as the outcome variables): choice of undergraduate major; student age; undergraduate institution ranking; UGPA growth; and whether the student completed their undergraduate studies in roughly a four-year period. As we describe above, UGPA growth is calculated as the difference between a student's first-year and final UGPA. For these analyses, we add the students' first year UGPA in order to account for their starting place.

Most notably, *we find that UGPA growth has a positive relationship with LGPA*. Holding all else constant, a student with a below average first-year UGPA who improves their UGPA by 0.2 grade points from the first year to the final year of their undergraduate studies is predicted to have a 1S LGPA 0.12 grade points higher than a similar student whose UGPA does not change and 0.24 grade points greater than a student whose UGPA diminished by 0.2 grade points.

Figure 8 shows the effect that UGPA growth has on 1S (the plot on the left) and final LGPA (the plot on the right), 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.)

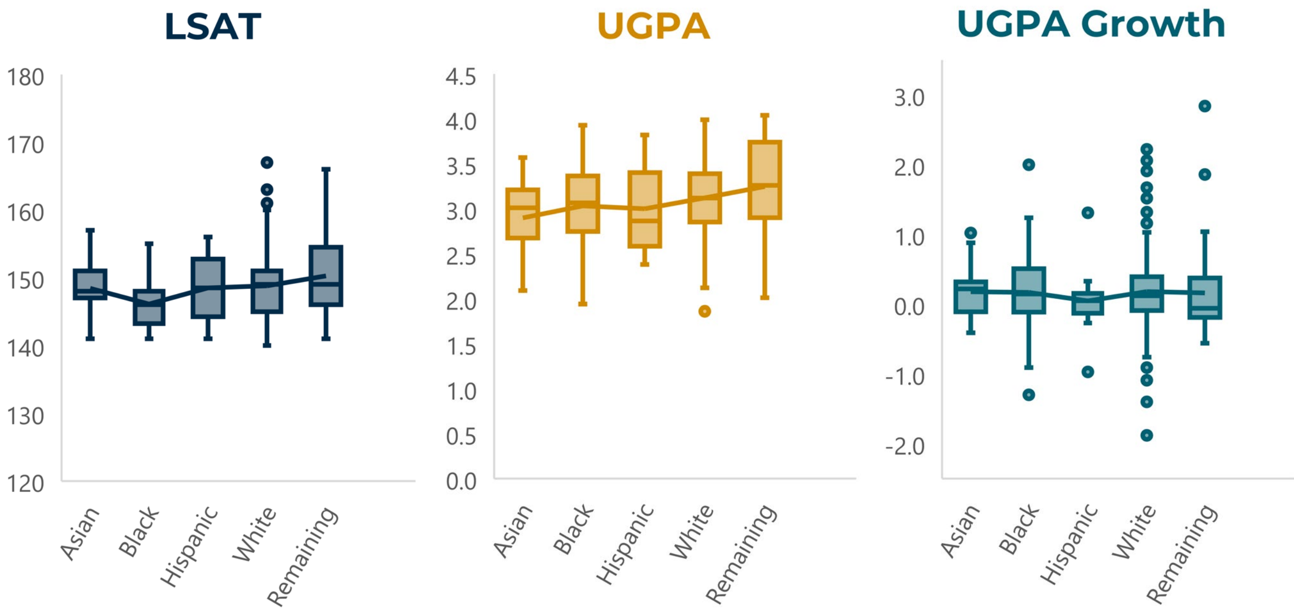
As indicated by the steepness of the slopes of the lines in Figure 8, our analyses find that UGPA growth (indicated by the blue line), regardless of the student's first-year UGPA, performs as well as or better than both LSAT score and final UGPA as predictors of academic success in the first year of law school.

FIGURE 8
UGPA Growth Predicts 1S and Final LGPA as Well as or Better Than Highest LSAT Score and Final UGPA



3. A More Equitable Approach to Admission Review?

LSAT score and final UGPA are often used to determine academic merit and promise when law schools evaluate candidates for admission. However, racial/ethnic performance gaps on standardized tests like the LSAT often yield inequitable admission outcomes, with historically underrepresented testers scoring lower than their White or Asian peers.



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predictor of law school academic performance compared to LSAT score and UGPA, suggests that UGPA growth may be a more equitable and inclusive metric for evaluating academic aptitude when making admissions decisions.

FIGURE 9

The Median and Mean UGPA Growth Vary Less Across Racial/Ethnic Groups Relative to LSAT Score and Final UGPA

C. DISCUSSION AND RECOMMENDATIONS

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

- LGPA improvement from the first semester to the end of law school is important to improving a student's likelihood of bar passage.
- LSAT score and UGPA have a modest positive association with first-time and ultimate bar passage. Comparatively, all LGPA measures are better predictors of bar passage.
- LSAT score and UGPA are modest predictors of law school performance.

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

- Properly contextualize preadmission factors when making admission decisions. Our results demonstrate that LSAT score and UGPA are positively correlated with 1S and 1L LGPA. Additionally, these incoming academic indicators become less predictive of academic performance and bar passage over time, and they are weaker predictors of 1L LGPA than UGPA growth. This suggests that, although LSAT score and UGPA are important, they are not determinative of academic and bar success. What happens in law school matters.

- Foster and cultivate a "growth mindset" among faculty and students. Our results indicate that not only is 1L LGPA one of the most important factors in predicting first-time and ultimate bar exam passage, but that LGPA growth is most influential during the first year of law school. Focusing on supporting at-risk students and helping them grow and maintain higher GPAs during (and beyond) year one may be one of the best intervention strategies for increasing bar passage rates. Although early interventions stand the best chance of maximizing law students' potential, student ability is never fixed, and students farther along in their studies are not a lost cause. Academic and bar interventions can and should occur after the first year and throughout law school.

- Continue to track LGPA across each year of law school to target interventions toward student with lower likelihood of first-time bar passage. 1S LGPA, 1L LGPA, final 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 final LGPA as a benchmark for bar success. The minimum predicted LGPA needed for a 75 percent chance of first-time bar passage increases from 2.34 in the first semester to 2.80 upon completing law school. Targeting interventions at each critical juncture of students' progression through law school, particularly in the second semester, may help your students, particularly those who show early sign of struggle, improve their chances of bar passage.

D. METHODOLOGY

1. Data

As noted above, your institution provided student data for 420 students that matriculated in 2012–2016, 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
- Matriculation year
- Undergraduate institution and major
- UGPA
- LSAT score
- Race
- Gender

2. Models

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

a. 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.

b. 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.

3. Variables

a. Outcomes

We use two sets of primary outcomes: students' 1S, 1L, and final 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").

b. Explanatory Variables

We use students' highest LSAT score, final (cumulative) UGPA, and UGPA growth to explain and make predictions about LGPA.

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, we are saying what the effect of UGPA growth is when first-year UGPA is held at the average (or other specified point) for all students.

For predictions about bar exam passage, we use the following academic success and preadmission variables:

- LGPA
  - First-semester
  - First-year
  - Final (cumulative)
  - Growth
- Credit Hours in:
  - Skills Courses
  - Doctrinal Courses
  - Clinic
- Highest LSAT Score
- UGPA
  - Final (cumulative)
  - Growth

As stated above in regard to UGPA growth, 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 worsen. Our models include 1S LGPA, which allows us to examine the effect of LGPA growth while holding 1S LGPA constant.

E. APPENDIX

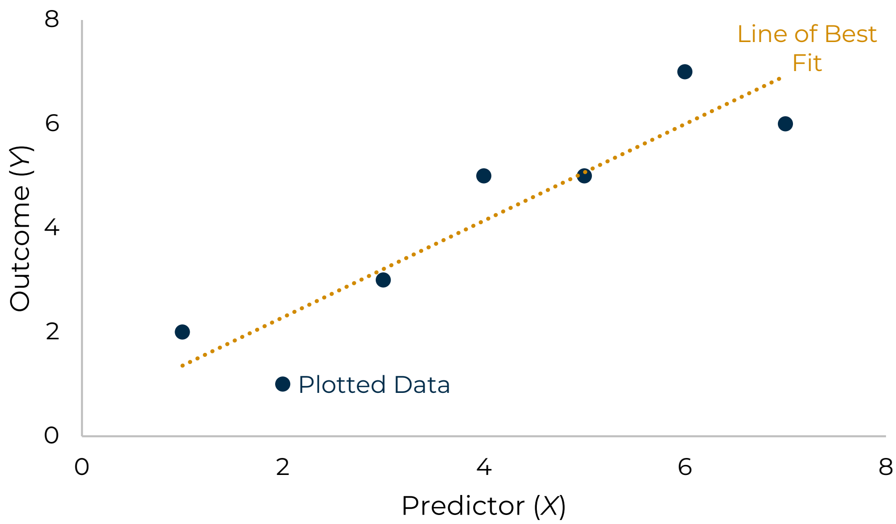
1. Interpreting Linear Regression

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. 2), 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 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. In order 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.

For example, the predictor variables UGPA and LSAT have coefficients of 0.32 and 0.50 in the first-semester LSAT & UGPA model. This means that our model predicts that an increase in UGPA from the minimum value reported in the sample to the maximum is associated with a 0.73 grade point increase in 1S LGPA. For a similar increase in LSAT, we would expect a 1.15 grade point increase. Since these variables are measured on the same scale, it is easier to recognize that LSAT has a larger effect than UGPA.

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, it 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.

2. Interpreting Logistic Regression

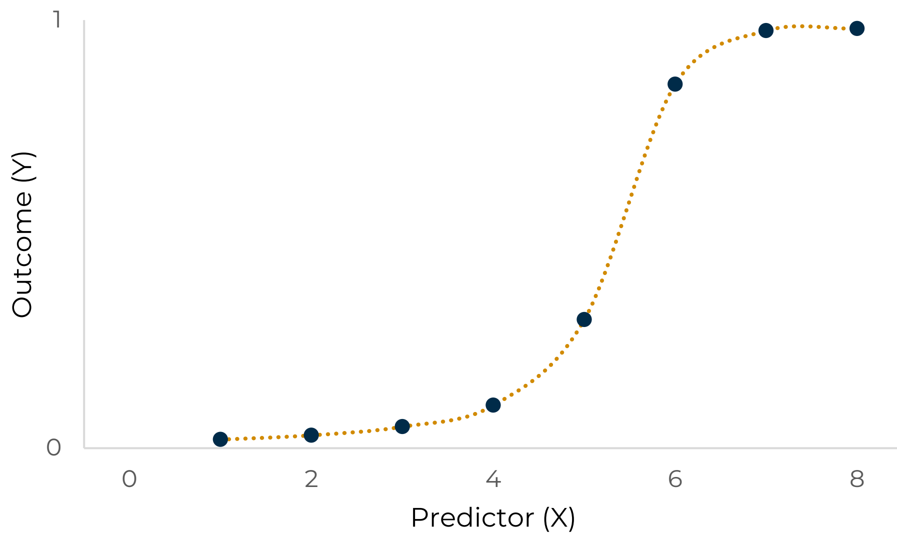
Logistic regression estimates the relationship between at least one independent variable (predictor) and one categorical dependent variable (outcome), the latter being a variable with a limited number of possible values. For these analyses, we focus exclusively on a specific form of logistic regression where the outcome is binary/dichotomous (that is, it can only take on one of two possible values). The 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 variable. Examples of control variables include race, gender, and age.

Logistic regression uses these independent, dependent, and control variables to map an 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.

FIGURE A.2

Logistic Regression Fits an S-Shaped (sigmoidal) Line



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

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.

To aid in interpretation, researchers will often convert these coefficients to odds ratios or provide predicted probabilities. In this report we use the latter.

Essentially, 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. A number of 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.

3. Statistical Significance

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

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.

TABLE A.1

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

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.

4. Summary Statistics

TABLE A.2

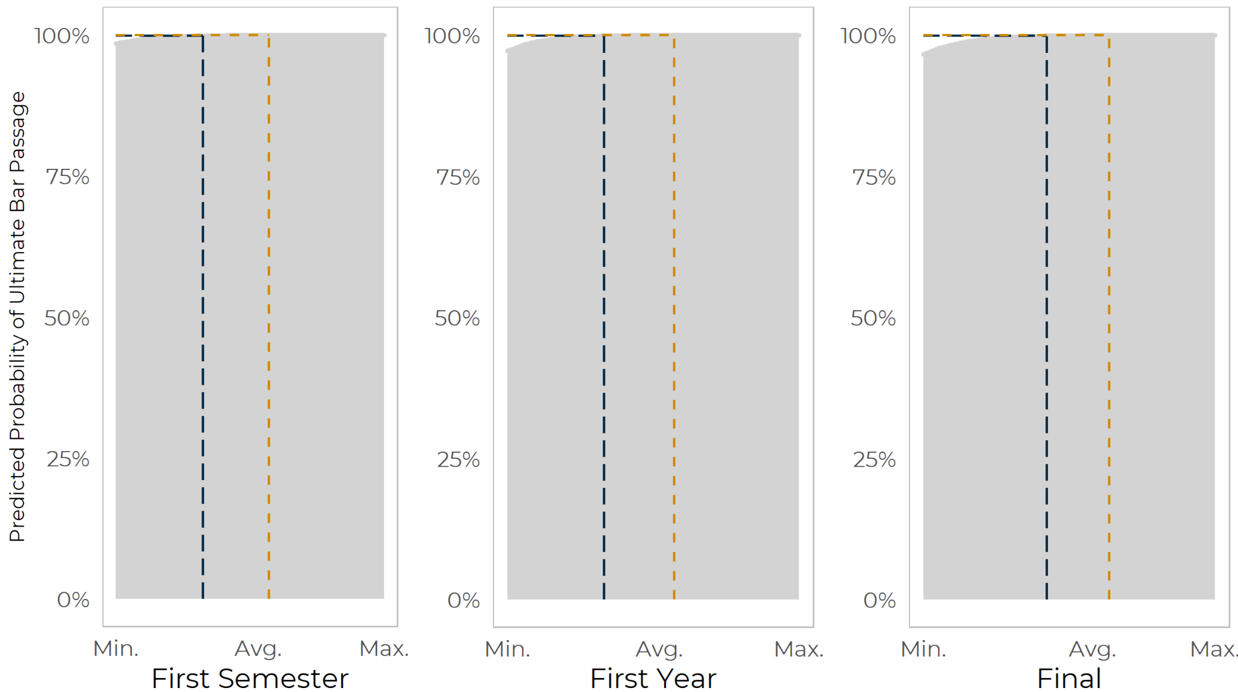
Summary Statistics

	Observations	Median	Mean	Standard Deviation	Minimum	Maximum
Full Sample						
Highest LSAT Score	1356	158	158	5	150	170
First-Year UGPA	1356	3.54	3.42	0.53	1.00	4.07
Final UGPA	1356	3.57	3.51	0.36	2.04	4.15
UGPA Growth	1356	0.04	0.1	0.38	-1.38	2.36
1S LGPA	1356	3.18	3.13	0.4	1.96	4.00
1L LGPA	1356	3.18	3.12	0.41	2.00	4.00
Final LGPA	1356	3.28	3.24	0.33	2.16	3.94
LGPA Growth	1356	0.11	0.09	0.18	-0.38	0.89

5. Additional Figures

FIGURE A.3

Ultimate Bar Passage Rates Increase as LGPA Increases



6. Regression Output Tables

TABLE A.3

Regression Results for First-Time Bar Passage
(LGPA Models)

	Principal Predictor Variable of Interest:			
	1S LGPA	1L LGPA	Final LGPA	LGPA Growth
1S LGPA	6.98 *			14.17 *
	[5.55; 8.42]			[12.05; 16.29]
1L LGPA		8.33 *		
		[6.73; 9.92]		
Final LGPA			11.64 *	
			[9.69; 13.59]	
LGPA Growth				9.07 *
				[7.21; 10.93]
Highest LSAT Score	2.00 *	1.76 *	1.45 *	
	[1.10; 2.90]	[0.83; 2.68]	[0.51; 2.40]	
Final UGPA	1.82 *	1.41 *	0.33	
	[0.69; 2.95]	[0.24; 2.58]	[-0.93; 1.60]	
Age	2.28			14.17 *
	[-1.27; 5.82]			[12.05; 16.29]
Age (squared)	-4.92 *	8.33 *		
	[-9.62; -0.22]	[6.73; 9.92]		
AIC	862.21	835.75	769.81	779.51
BIC	940.40	913.94	847.99	842.05
Num. obs.	1356	1356	1356	1356

Note: *** p < 0.001; ** p < 0.01; * p < 0.05; All continuous variables are scaled 0-1.

TABLE A.4

Regression Results for First-Time Bar Passage
(Preadmission Models)

	Principal Predictor Variable of Interest:	
	LSAT/UGPA	UGPA Growth
Highest LSAT Score	3.34 *	3.35 *
	[2.52; 4.16]	[2.52; 4.18]
Final UGPA	2.75 *	
	[1.75; 3.75]	
UGPA Growth		3.15 *
		[0.76; 5.53]
Race: White		-0.89
		[-2.07; 0.30]
Race: Remaining	973.38	971.56
	1035.93	1044.54
Age	3.34 *	3.35 *
	[2.52; 4.16]	[2.52; 4.18]
AIC	2.75 *	
BIC	[1.75; 3.75]	
Log Likelihood	-474.69	-471.78
Deviance	949.38	943.56
Num. obs.	1356	1356

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; All continuous variables are scaled 0-1.

TABLE A.5

Regression Results for Ultimate Bar Passage

	Principal Predictor Variable of Interest:		
	1S LGPA	1L LGPA	Final LGPA
1S LGPA	7.33 *		
	[5.29; 9.37]		
1L LGPA		8.84 *	
		[6.58; 11.11]	
Final LGPA			7.19 *
			[5.30; 9.07]
Highest LSAT Score	1.69 *	1.38 *	-0.43
	[0.41; 2.96]	[0.06; 2.70]	[-1.68; 0.82]
Final UGPA	1.90 *	1.43	-1.12
	[0.33; 3.47]	[-0.20; 3.06]	[-2.79; 0.55]
Race: White	498.83	483.09	508.01
	566.59	550.85	570.56
Race: Remaining	-236.42	-228.54	-242.01
	472.83	457.09	484.01
AIC	498.83	483.09	508.01
BIC	566.59	550.85	570.56
Num. obs.	1356	1356	1356

Note: *** p < 0.001; ** p < 0.01; * p < 0.05; All continuous variables are scaled 0-1.

TABLE A.6

Regression Results for LGPA

	Outcome Variable:					
	1S LGPA		1L LGPA		Final LGPA	
	LSAT/UGPA Model	UGPA Growth Model	LSAT/UGPA Model	UGPA Growth Model	LSAT/UGPA Model	UGPA Growth Model
Highest LSAT Score	0.57 *	0.58 *	0.58 *	0.58 *	0.47 *	0.47 *
	[0.51; 0.64]	[0.51; 0.65]	[0.52; 0.65]	[0.52; 0.65]	[0.41; 0.52]	[0.42; 0.52]
Final UGPA	0.51 *		0.57 *		-0.57 *	
	[0.41; 0.61]		[0.47; 0.66]		[-0.98; -0.16]	
Final UGPA (squared)					0.91 *	
					[0.58; 1.23]	
UGPA Growth		0.82 *		0.95 *		0.93 *
		[0.58; 1.06]		[0.72; 1.18]		[0.74; 1.12]
Race: White		0.76 *		0.84 *		0.81 *
		[0.62; 0.91]		[0.70; 0.98]		[0.69; 0.92]
Race: Remaining				0.09		
				[-0.03; 0.22]		
Year 1 UGPA	0.49	0.50	0.53	0.53	0.52	0.51
	0.49	0.49	0.53	0.53	0.51	0.50
Age	1356	1356	1356	1356	1356	1356
	0.57 *	0.58 *	0.58 *	0.58 *	0.47 *	0.47 *
R^2	[0.51; 0.64]	[0.51; 0.65]	[0.52; 0.65]	[0.52; 0.65]	[0.41; 0.52]	[0.42; 0.52]
Adj. R^2	0.51 *		0.57 *		-0.57 *	
Num. obs.	[0.41; 0.61]		[0.47; 0.66]		[-0.98; -0.16]	

Note: *** p < 0.001; ** p < 0.01; * p < 0.05; All continuous variables are scaled 0-1.

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