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Ruth Bader Ginsburg SCHOOL OF LAW

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BAR EXAM INITIATIVE

REPORT FOR RUTH BADER GINSBURG SCHOOL OF LAW

OCTOBER 2024

EXECUTIVE SUMMARY

This report conveys the results from Ruth Bader Ginsburg School of Law's participation in the AccessLex Bar Exam Success Analyses initiative. These data-driven insights are intended to help:

Identify those at risk of low academic performance and failing the bar exam.

Develop strategies to target these students and tailor interventions accordingly.

The analyses use data your institution provided on 1,037 RBG Law students who matriculated for the first time between 2015 and 2020. The report explores the extent to which (1) various preadmission factors predict early academic performance and (2) law school performance and course-taking predict first-time bar exam performance. Key findings are summarized below.

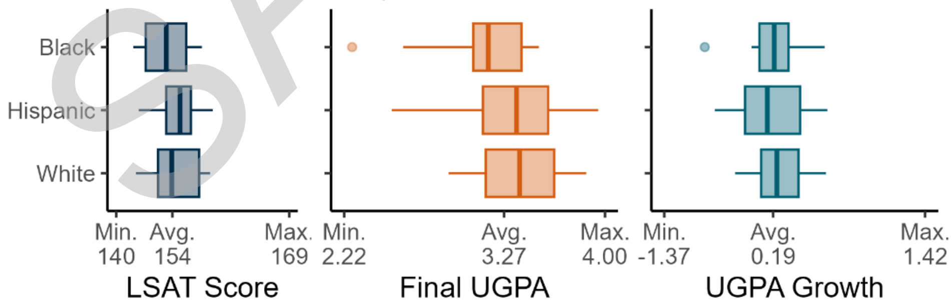
1. UGPA Growth Predicts Law School Success Comparably to LSAT and UGPA.

LSAT Score and Final UGPA

To an extent, highest LSAT score and final undergraduate GPA (UGPA) help predict 1L GPA (p. 9).

UGPA Growth

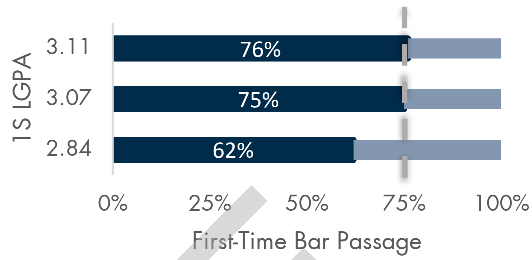
However, UGPA growth (or trajectory from their first year to graduation) predicts 1L GPA **as well as** LSAT score and final UGPA, without the same demonstrated racial disparities (p. 10, p.27).



2. What Happens in Law School Matters.

Law School GPA

After matriculation, students with 1S LGPAs below **3.07** have ***less than a 75% chance*** of passing the bar on their first attempt (p. 14). This may be a useful threshold for early intervention.



Coursework

Grades and credit-hour loads in **doctrinal** bar coursework positively influence first-time bar passage (see p.19). Higher credit-hour loads in **externships** enhance bar passage odds for students with above-average 1L LGPAs, while **skills** courses benefit students with below-average 1L LGPAs (p.23).

3. Student Potential Is Not Static.

LGPA Growth

Students who improve their grades during law school are more likely to pass the bar exam than students who do not. A typical student who **improves** their LGPA by **0.27 grade points** from the first semester to graduation increases their predicted probability of first-time bar passage by 19 **percentage points** (p. 17).

Recommendations:

1. Properly contextualize preadmission factors when making admissions decisions.
2. Consider including UGPA growth in admissions decisions using an index that combines LSAT score, final UGPA, and UGPA growth (p.27)
3. Track LGPA across each year of law school to target interventions, encouraging growth mindset.
4. Tailor course recommendations to 1L performance.

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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:

Law School GPA (LGPA)	Coursework (grades/credits)	Preadmission factors (LSAT/UGPA)

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.

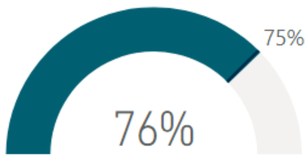
a. School Overview

Using data from our free tool, Analytix by AccessLex®, we begin by providing a brief overview of key trends at Ruth Bader Ginsburg School of Law, which we illustrate in a dashboard on the next page. This overview is intended to serve as a backdrop for the more detailed and specific findings discussed later in this report.

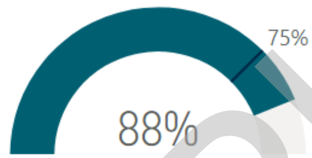
As shown in the top row of the dashboard, RBG Law's average first-time bar passage rate across 2014-2022 is 76%, and its ultimate bar passage rate is 88% across 2017-2021. RBG Law's first-time bar passage rate has remained relatively unchanged in each of the past three years (as shown in the second row), but the median LSAT score and median final UGPA have slightly increased, while admission rates have remained consistent and matriculation rates have seen a small decline (bottom row).

KEY INDICATOR DASHBOARD

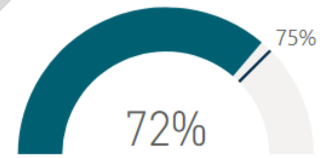
Average First-Time Bar Passage
2014 - 2022



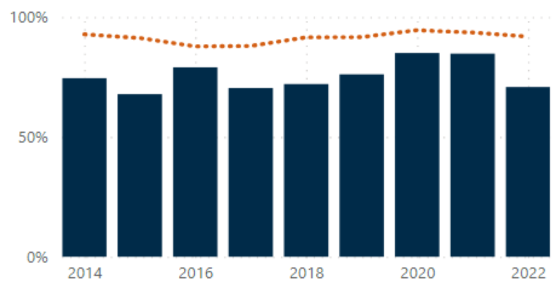
Average Ultimate Bar Passage
2017 - 2021



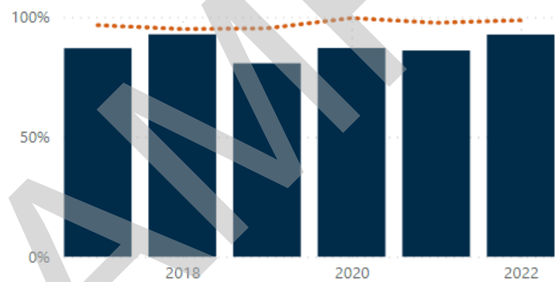
Average Employment Rate (Bar Passage Required)
2014 - 2022



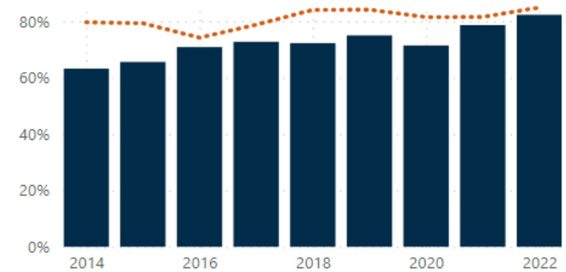
First-Time Bar Passage Rate
2014 - 2022



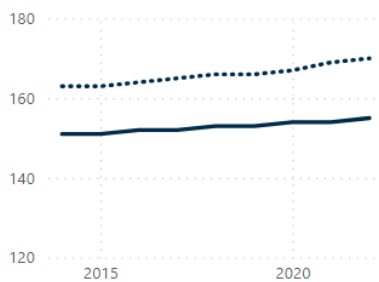
Two-Year Ultimate Bar Passage Rate
2014 - 2022



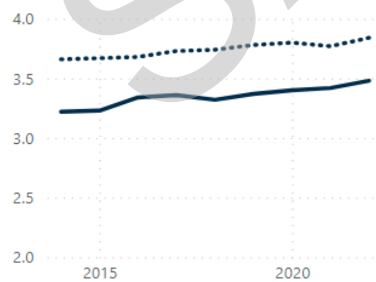
Employment Rate (Bar Passage Required)
2014 - 2022



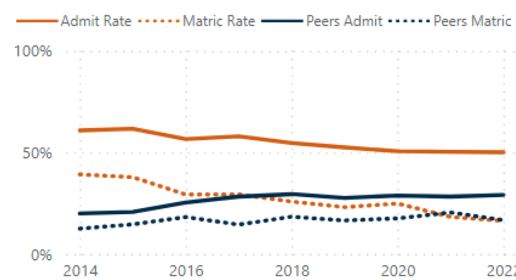
Median LSAT Score
2014 - 2022



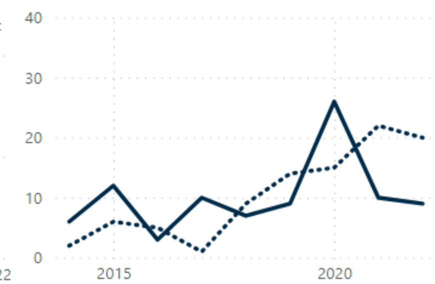
Median Final Undergraduate GPA
2014 - 2022



Admission and Matriculation Rates
2014 - 2022



Total 1L Attrition
2014 - 2022



Note: For each figure in the middle and bottom rows, we include the trend of the median value among a group of peer schools, which is represented by a dotted line. The group of peer schools comprises: Elena Kagan School of Law, John Roberts Law School, and Sonia Sotomayor College of Law.

b. Analytical Approach

This report aims to identify predictors of LGPA and bar exam performance (our "outcomes"). Predictors of each outcome are summarized separately in the results that follow. All analyses use deidentified data submitted by your institution in March 2024. These data comprise 1,037 students who matriculated in 2015 through 2020. Of the 1,037 individuals, 41 were dismissed and 29 transferred to another school (see Table 4 in the Appendix).

These data comprise 1,037 students who matriculated in 2015 through 2020.

To analyze 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:

- final UGPA and LSAT score;
- 1L LGPA;
- LGPA growth;

- Credit hours earned in doctrinal, skill- and clinic-based, legal writing, and externship courses;
- LGPAs in specific upper-level doctrinal courses.

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 negligible, modest, moderate, and substantial based on the criteria as shown below in Table 1. These classifications are intended to provide context regarding *practical* significance of the findings and are independent of *statistical* significance.

TABLE 1

Thresholds for Determining Magnitude of Predictive Effects

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 0.35 points	**OR**	**10 or fewer percentage-points**	**THEN**	**Negligible**
	0.35–1 point		**11–30 percentage points**		**Modest**
	1.1–2 points		**31–50 percentage points**		**Moderate**
	More than 2 points		**51 or more percentage points**		**Substantial**

RESULTS

a. What Predicts Law School Performance?

We begin by investigating the extent to which several preadmission factors predict 1L LGPA. The preadmission variables we consider are: highest LSAT score, final UGPA, UGPA growth, undergraduate institution (UGI) admission rate,[1] and whether the student transferred undergraduate institutions. For these analyses, we include several control variables — factors that are statistically related to both 1L LGPA *and* the preadmission variable(s) in which we are interested. For example, we would include a control variable for age if we found evidence of a relationship between it, 1L LGPA, and LSAT score.

We consider the following control variables:

- race,
- gender,
- age at matriculation,
- number of years to complete their undergraduate degree, and
- number of LSAT attempts.

However, only those control variables with the requisite statistical relationships with 1L LGPA and the preadmission variable are included in the models.

i. LSAT Score and UGPA

We find that higher LSAT scores and final UGPAs are associated with higher 1L LGPAs. This model controls for race, age at matriculation, UGI selectivity (admission rate), number of years to complete their undergraduate degree, and number of LSAT attempts.

[1] In situations where a student attended more than one UGI, we use the admission rate of the UGI from which the student graduated.

Specifically:

	An increase in **LSAT score** (points) of…		
	1	5	11
…is associated with an increase in predicted 1L LGPA of…	0.02	0.16	0.32

	An increase in **final UGPA** (grade points) of…		
	0.10	0.50	1.00
…is associated with an increase in predicted 1L LGPA of…	0.04	0.17	0.34

Our analyses indicate that LSAT score and final UGPA similarly predict 1L LGPA, as indicated by the steepness of the lines in Figure 1 (see next section).

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. Furthermore, early results indicate that UGPA growth — the difference between a student's first year and final UGPA — is associated with 1L LGPA.[2] We, therefore, investigate the relationship between UGPA growth and 1L LGPA at RBG Law.

[2] In a new report, we find that GPA improvement during undergraduate study is associated with higher predicted 1L LGPAs, and decreased odds of 1L attrition. Jason M. Scott, Andrea M. Pals, & Paige WIlson, *Measuring "Up": The Promise of Undergraduate GPA Growth in Law School Admissions* (AccessLex Inst. Rsch. Paper No. 24-03, 2024), https://dx.doi.org/10.2139/ssrn.4789416.

For these analyses, we add the students' first-year UGPA to account for their starting place, while also controlling for:

- race,
- age at matriculation,
- undergraduate institution selectivity (admission rate),
- and number of years to complete their undergraduate degree.

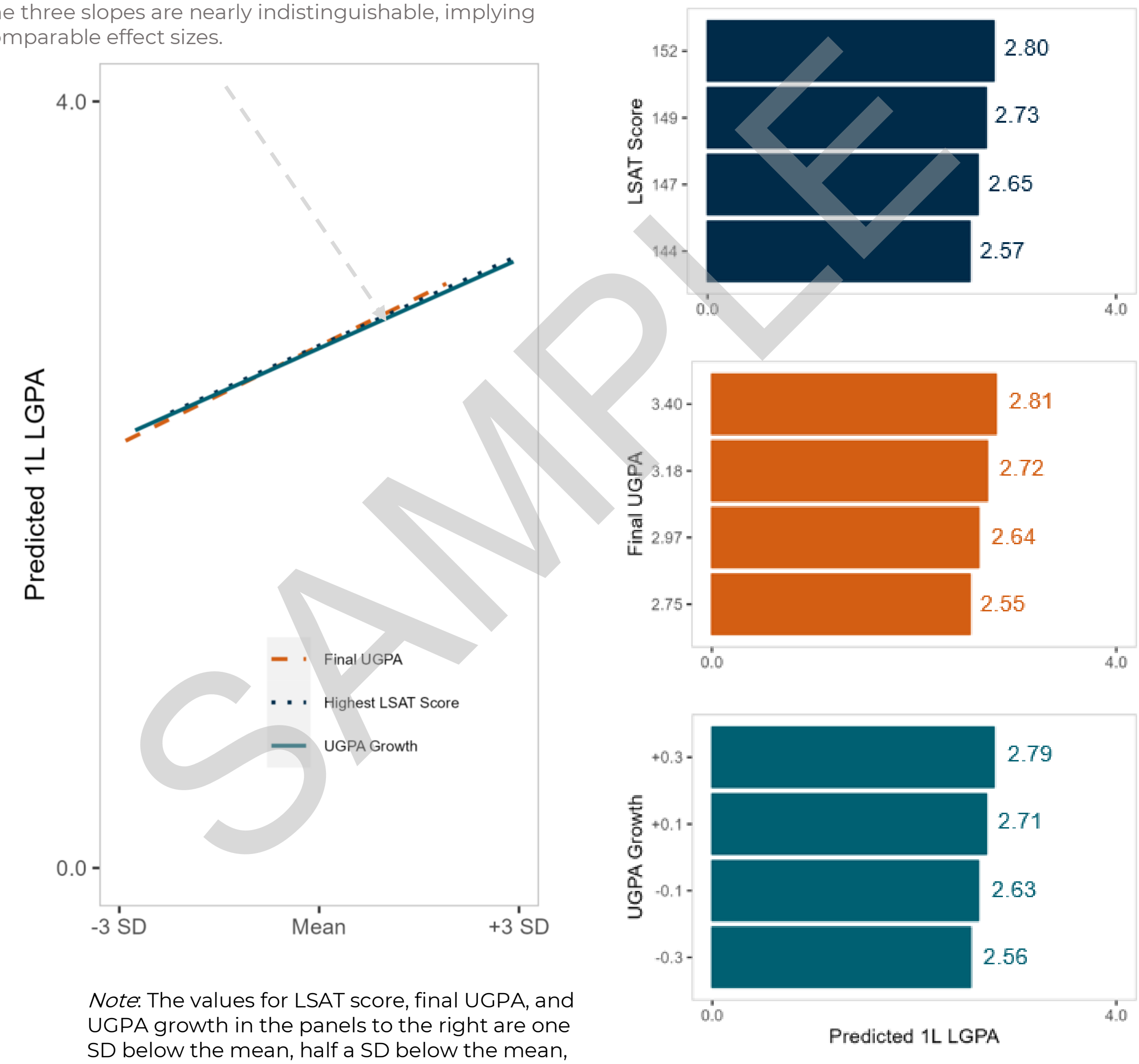
UGPA growth has a positive relationship with 1L LGPA at RBG Law.

Holding all else constant, a student with a below-average first-year UGPA who improves their UGPA by half a standard deviation (0.19 grade points) from the first year to the final year of their undergraduate studies is predicted to have a 1L LGPA 0.21 grade points higher than a similar student whose UGPA does not change and 0.41 grade points greater than a student whose UGPA diminished by 0.19 grade points.

FIGURE 1

UGPA Growth Predicts 1L LGPA as Well as or Better Than Highest LSAT Score and Final UGPA

The three slopes are nearly indistinguishable, implying comparable effect sizes.



Note: The values for LSAT score, final UGPA, and UGPA growth in the panels to the right are one SD below the mean, half a SD below the mean, at the mean, and half a SD above the mean.

Figure 1 illustrates the relationships between 1L LGPA and LSAT score, final UGPA, and UGPA growth. The graph on the left compares the size of the predictive effects of LSAT score (dotted navy line), final UGPA (dashed orange line), and UGPA growth (solid teal line). UGPA growth does not vary by first-year UGPA. The steepness of the slope of the line indicates the size of the predictive effect; steeper lines indicate stronger effects, and vice versa. The panels to the right show students' predicted 1L LGPA values based on different levels of their LSAT score, final UGPA, and UGPA growth (for students with average first-year UGPAs).

As indicated by the steepness of the slopes of the lines and the similarity of the predicted 1L LGPA values in Figure 1, our analyses find that UGPA growth, 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.

b. What Predicts First-Time Bar Exam Performance?

In this section, we investigate the extent to which academic performance and course-taking predict first-time bar passage.

We create several models for these analyses, each of which includes its own set of control variables. 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/ethnicity, vary.

Since the predictor variables are different in each model, the control variables utilized may also be different. If a control variable is included in one model but not in another, it means that variable had the requisite statistical relationships with the variables in one model but not the other. In each case, we consider the following control variables:

- race,
- gender,
- age at matriculation,
- class rank,
- administration period,
- and jurisdiction of first bar exam attempt.

i. 1S, 1L, and Final LGPA

We first consider the extent to which first-semester (1S), 1L, and final LGPA predict first-time bar passage.

We find that higher 1S, 1L, and final LGPAs predict greater likelihoods of first-time bar passage, and conversely, that lower LGPAs predict lesser likelihoods of bar passage. Each relationship is statistically significant.

It is important to note a few key observations regarding these relationships. Students below the following LGPA thresholds have less than a 75% chance of passing the bar on their first attempt:

1S LGPA	1L LGPA	3L LGPA
3.07 grade points.	3.07 grade points.	3.25 grade points.

This final LGPA threshold might be a useful 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 3.25 final LGPA might be a helpful monitoring effort. Students who still fall below this threshold at graduation may benefit most from postgraduate bar preparation.

Below the above thresholds, even modest increases in LGPA are associated with marked increases in predicted probability of first-time bar passage. Beyond this point, the gains in likelihood of bar passage begin to plateau, which means that even relatively large increases in LGPA are associated with only slight increases in predicted probability of first-time bar passage.

To quantify the importance of LGPA changes below these thresholds, we compare the predicted probability of bar passage for a student with a below-average LGPA to one with an average LGPA.

We find that:

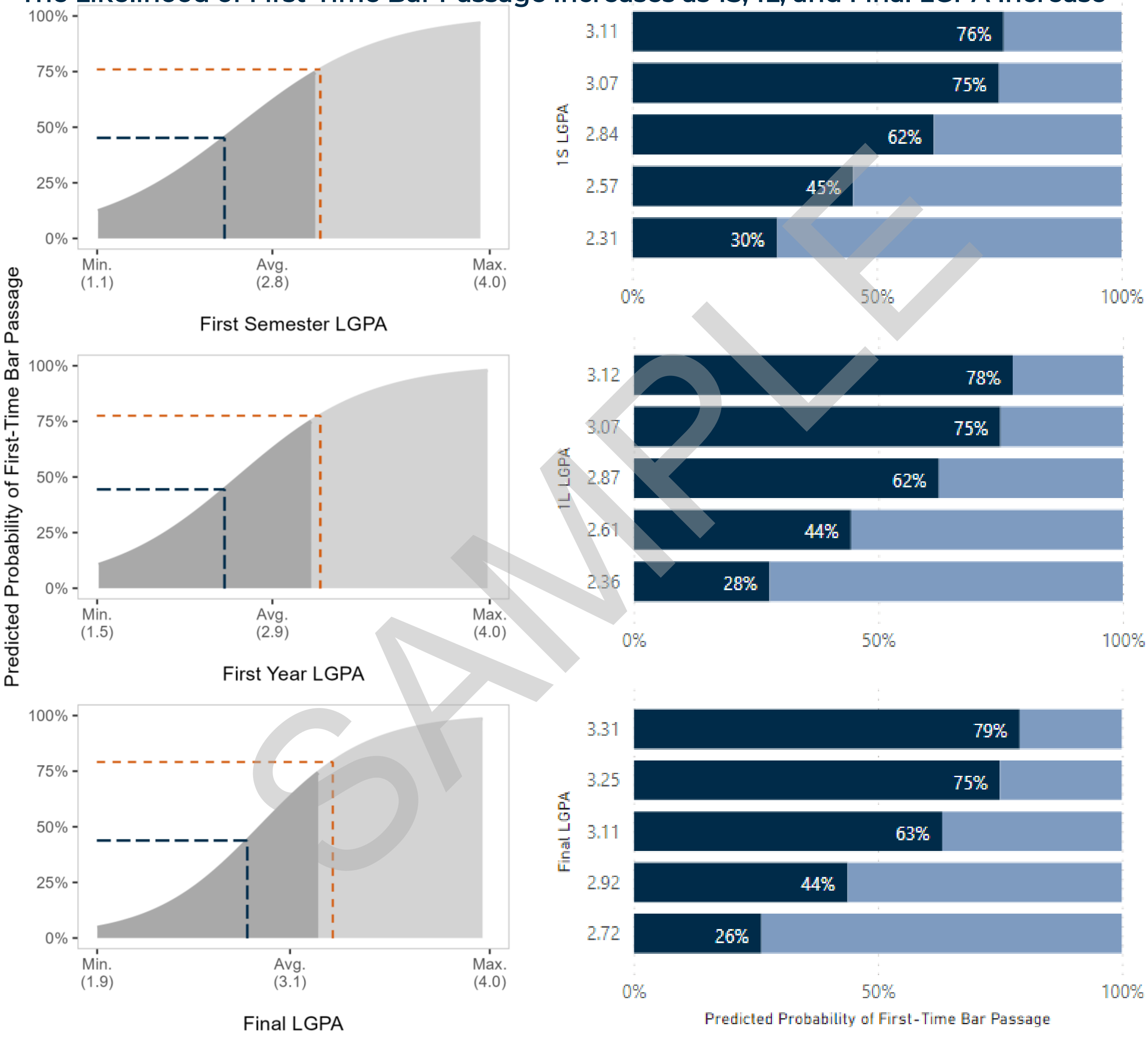
A one-standard deviation LGPA increase in...	1S LGPA	1L LGPA	3L LGPA
...is associated with an increase in predicted probability of first-time bar passage of...	+ 32 percentage points	+ 34 percentage points	+ 37 percentage points

Figure 2 illustrates these relationships between first-time bar passage and LGPA. In the graphs on the *left*, we show how changes in LGPA (1S LGPA on top, 1L LGPA in the middle, and final LGPA on bottom) correspond with changes in the predicted probability of first-time bar passage. We note several key points on the figure: The thresholds below which a student's predicted probability of bar passage falls below 75 percent, represented by the dark gray area under the curve; The predicted probability of bar passage for students with above average (where the dashed orange lines intersect the y-axis) and below average LGPAs (where the dashed blue lines intersect the y-axis) and the difference in predicted probabilities between them.

In the graphs on the *right* of Figure 2, we show the specific predicted probabilities of first-time bar passage for students with a range of LGPAs (one standard deviation below the mean, half a standard deviation below the mean, at the mean, at the value that indicates 75 percent probability of bar passage, and half a standard deviation above the mean in 1S, 1L, and final LGPA values for your school).

FIGURE 2

The Likelihood of First-Time Bar Passage Increases as 1S, 1L, and Final LGPA Increase



ii. LGPA Growth

Given the sizable differences in predicted probabilities of first-time bar passage between students with 1S LGPAs below 2.8 and 1L LGPAs below 2.9 grade points, we next investigate the extent to which LGPA growth — the difference between a student's 1S and final LGPA — is associated with first-time bar performance, holding LSAT score, UGPA, year of first bar exam attempt, and age at matriculation constant.[3] In this model, we also include 1S LGPA to account for a student's starting place.

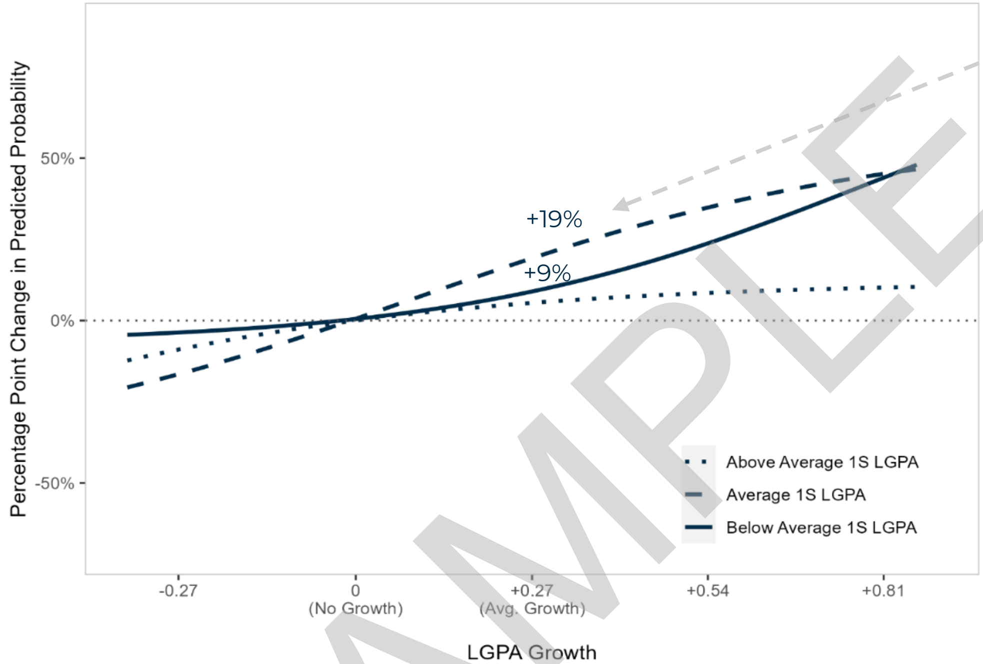
We find that greater growth is associated with greater predicted likelihoods of passing the bar and that negative growth (or a decrease in LGPA) is associated with lower predicted likelihoods.

Figure 3 (next page) shows how a student's predicted probability of first-time bar passage changes as their LGPA grows (moving to the right on the x-axis away from 0) or declines (moving to the left, away from 0) given their 1S LGPA. The solid blue line represents a student with a below-average 1S LGPA (2.31 at RBG Law), the dashed line represents a student with an average 1S LGPA (2.84), and the dotted line represents a student with an above-average 1S LGPA (3.38).

[3] In a previous report, 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. Aaron N. Taylor, Jason M. Scott, & Joshua L. Jackson, *It's Not Where You Start, It's How You Finish: Predicting Law School and Bar Success*, 21 J. HIGHER EDUC. THEORY & PRAC. 103 (2021), https://www.proquest.com/openview/013929c81e0a389d3c0a7afe37da7bf2/1?pq-origsite=gscholar&cbl=766331.

FIGURE 3

LGPA Improvement Is Associated With Meaningful Increases in the Predicted Probability of First-Time Bar Passage



A student with an average first-semester GPA who improves their GPA by 0.27 grade points has a predicted probability of first-time bar passage 19 percentage points higher than a student whose GPA did not grow.

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 blue line). Among these students, one who improves their LGPA (moves to the right along the x-axis) by 0.27 grade points from their first semester to graduation — the average increase for your students — is predicted to have a probability of first-time passage 19 percentage points higher than a student with a similar 1S LGPA whose LGPA did not grow.

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 0.27 grade points has a predicted probability of first-time bar passage 9 percentage points greater than a student with no growth.

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. Doctrinal LGPA

Generally, we find that doctrinal LGPA — overall and in each course — has a strong, positive, and statistically significant effect on bar passage.

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 all doctrinal courses;
- In required 1L doctrinal courses only;
- In each of the following Upper-Level doctrinal courses:
    - Article 9 (Secured Transactions),
    - Business Associations,
    - Conflict of Laws,
    - Criminal Procedure,
    - Evidence,
    - Family Law, and
    - Trusts and Estates;
- Collectively across all Upper-Level doctrinal courses; and
- In all other doctrinal courses.

When exploring each of these doctrinal LGPA variables, we control for race, and jurisdiction and year of first bar examination attempt.

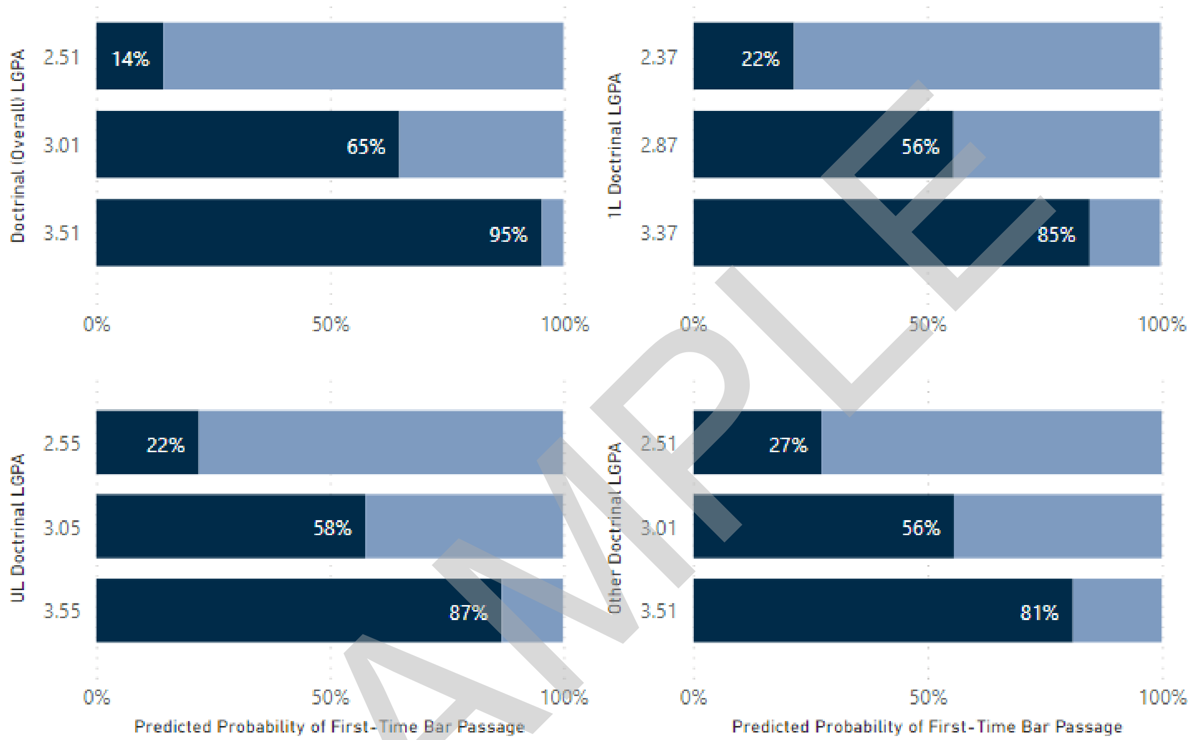
Generally, we find that doctrinal LGPA — overall and in each course — has a positive, practically significant effect on bar passage. Furthermore, each of these effects is statistically significant.

Overall doctrinal LGPA (measured across all doctrinal courses) has the strongest relationship with bar passage. Students with a doctrinal course LGPA of 3.51 have a probability of first-time bar passage 30 percentage points higher than a student with a 3.01 LGPA (95 versus 65). First-year and upper-level doctrinal course LGPA have the next strongest relationship with bar passage, with a 29-percentage point difference each. Students with a 1L doctrinal course LGPA of 3.37 have an 85% predicted probability of first-time bar passage, while a student with a 2.87 LGPA has a 56% predicted probability of first-time passage.

Figure 4 and Figure 5 illustrate the extent to which the predicted probability of first-time bar passage changes in relation to LGPA for the individual doctrinal courses we examined, comparing the predicted probability of bar passage for students with three different LGPAs: the average LGPA in a particular course and 0.5 grade points above and below the average.

FIGURE 4

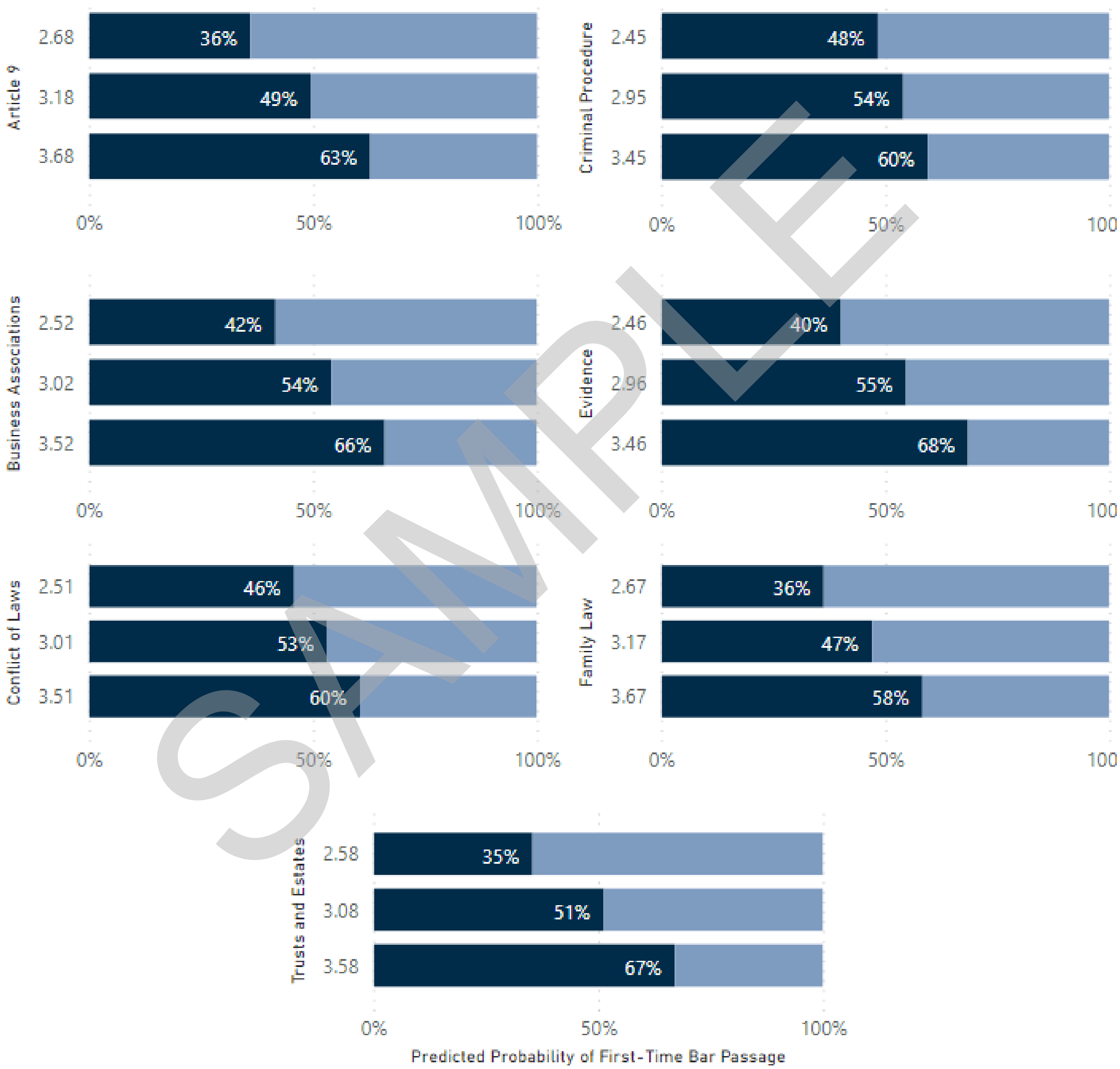
The Predicted Probability of Bar Passage Increases as Doctrinal Course LGPA Increases



Note: GPA values represent 0.50 grade points below the mean, at the mean, and 0.50 grade points above the mean for each course type.

FIGURE 5

The Predicted Probability of Bar Passage Increases as Course LGPA Increases



iv. *Credit Hours by Course Type*

In this section, we examine the extent to which course credits earned in clinic- and skills-based courses, doctrinal courses, externships, legal writing courses, and other elective courses predict first-time bar passage.

These models control for:

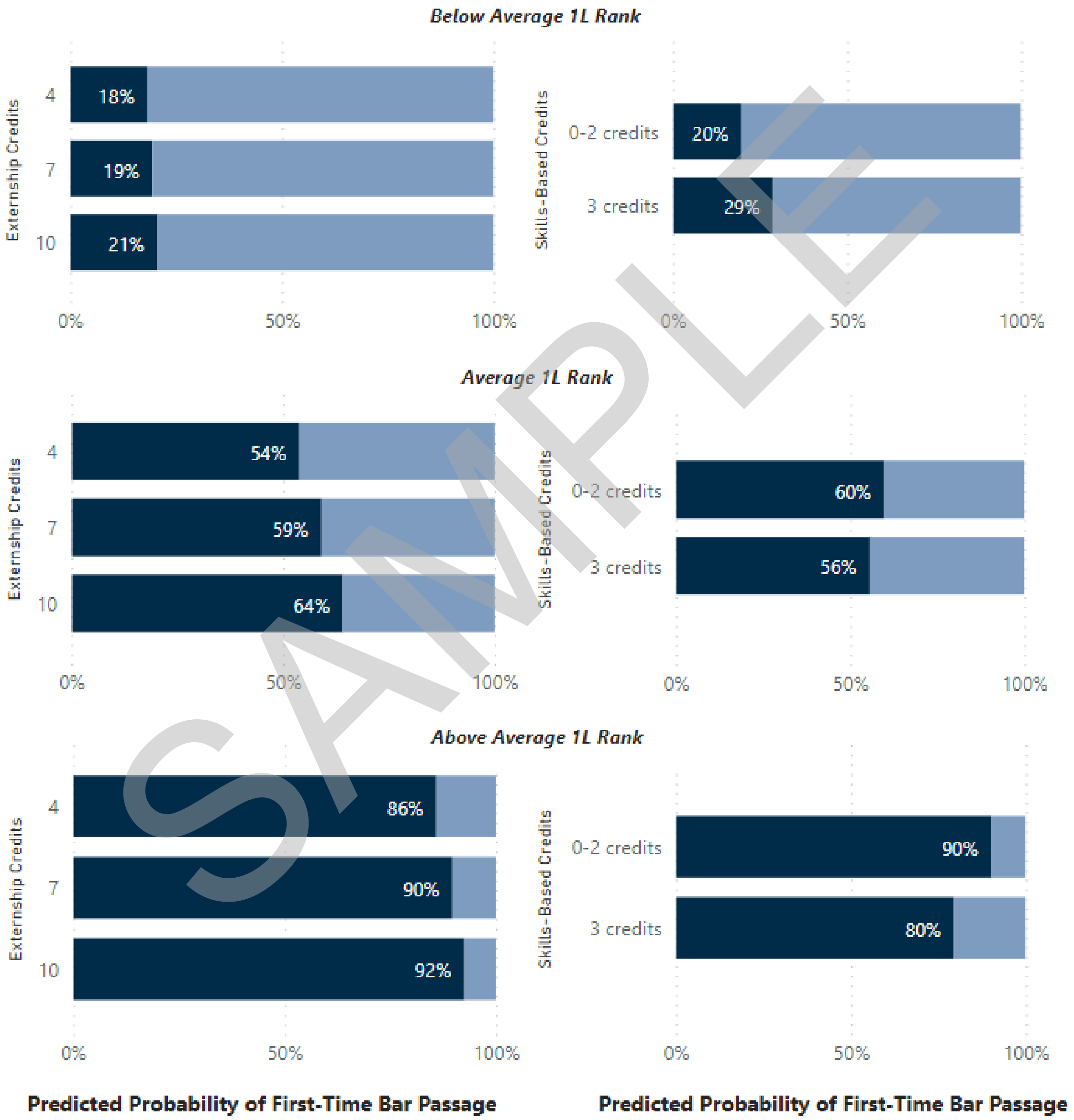
- race,
- age at matriculation,
- 1L class rank,
- jurisdiction, and
- year of first bar examination attempt.

On average, we find that total credit hours earned across all doctrinal courses, skills- and clinic-based courses, or legal writing courses are not meaningfully related to the odds of first-time bar passage. Conversely, students who earn more credit hours in externships have higher predicted probabilities of first-time bar passage. None of the relationships are statistically significant.

However, the relationships between first-time bar passage and skills-based courses and externships vary by a student's 1L class rank.

FIGURE 6

The Predicted Probability of Bar Passage Changes With Credits Earned in Externships and Skills-Based Courses



Among those with below-average 1L LGPA, more credit hours in skills-based coursework are associated with higher predicted probabilities of first-time bar passage. Meanwhile, students with average or above-average 1L rankings benefit more from externships.

For externships, more credits hours are associated with greater predicted probabilities of first-time bar passage for those with average and above-average 1L class ranks. Among those with below-average 1L class ranks, there does not appear to be a meaningful relationship between credits hours in externships and the odds of first-time bar passage.

For skills-based courses, more credit hours are associated with greater predicted probabilities of bar passage for those with below-average 1L class ranks. Among those with average or above-average 1L ranks, the number of credit hours earned in these courses is not correlated with first-time bar passage.

Figure 6 illustrates the extent to which the number of credit hours earned in externships and skills-based courses relate to the probability of first-time bar passage given a student's 1L class rank (below-average, average, and above-average).

Despite the average negative association between skills-based courses and bar passage, these courses are not necessarily 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 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 and appear to be particularly helpful for students who underperform in their 1L year.

v. LSAT Score and UGPA

Below, we examine the extent to which LSAT score and UGPA predict first-time bar performance, holding race, gender, and LGPA constant.[4] We then contextualize the size of these effects by comparing them with those achieved when using LGPA to predict bar passage.

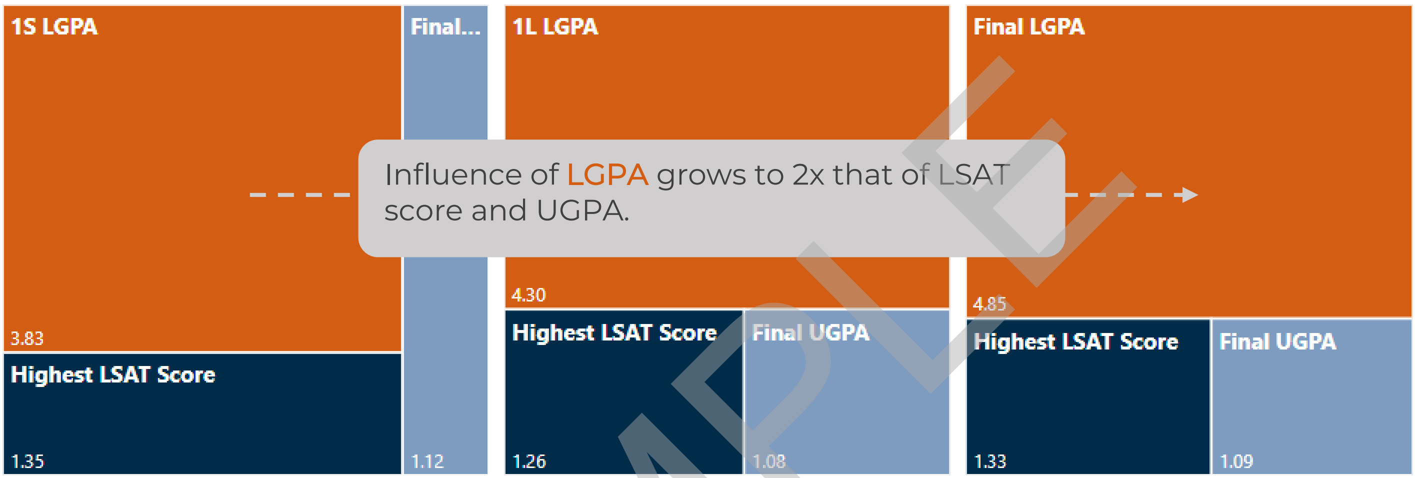
We find that highest LSAT score and final UGPA do not have a meaningful effect on the predicted probability of bar passage when we control for 1S, 1L, or final LGPA.

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. The size of the effect that preadmission factors have on bar passage are around a third of the size of 1S and 1L LGPA, and a fourth of the size of final LGPA. 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.

[4] In a recent AccessLex report, we find that LGPA explains nearly all of the statistical relationship between LSAT score, UGPA, and first-time bar passage. We therefore include LGPA when examining this relationship. Jason M. Scott, Andrea M. Pals, & Paige Wilson, *Predicting Bar Success: The Mediating Effects of Law School GPA* (AccessLex Inst. Rsch. Paper No. 24-02, 2024), https://dx.doi.org/10.2139/ssrn.4789411

FIGURE 7

1S, 1L, and Final LGPA Have Much Stronger Relationships With First-Time Bar Passage Than Either Final UGPA or Highest LSAT Score



Note: The size of the boxes represents the proportionate size of the predictor's effects on first-time bar passage relative to each other, with the numbers indicating the variables' odds ratios in their respective models.

c. A More Equitable Approach to Admission Review?

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

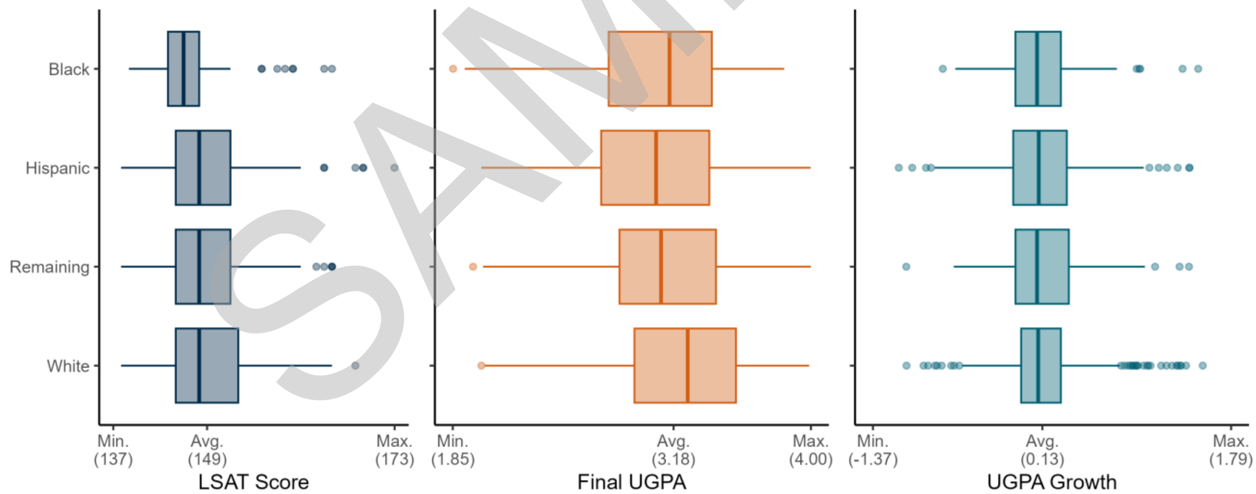
Figure 8 illustrates the distribution of highest LSAT scores, final UGPAs, and UGPA growth values for Black, Hispanic, and White students, and students from all remaining racial/ethnic groups at RBG Law. The box represents the middle 50 percent of the observed values, with the 25th percentile on the 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.

Recent research from AccessLex indicates that UGPA growth may serve as a useful predictor of early law school academic performance.

As shown in Figure 8, among those 1,037 students in our sample who matriculated in 2015–2020, 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 149 and final UGPA of 3.22, compared to 147 and 3.08 for Black students, respectively. On the other hand, the variation in median UGPA growth values between White and Black students is 0.02 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



Recent research from AccessLex indicates that UGPA growth may serve as a useful predictor of early law school academic performance. When used in conjunction with highest LSAT score and final UGPA to generate a single index score, we find that schools can predict first-year academic performance as well as when using a traditional index comprising highest LSAT score and final UGPA only. Our research indicates that doing so may result in the enrollment of more racially diverse classes while retaining a school's median LSAT score and final UGPA.

The most effective index for your school consists of 50% LSAT score, 30% final UGPA, and 20% UGPA growth.

To assist your institution in applying a similar approach, we use the data your school provided to calculate such an index, which we call the Academic Potential Index (or API), that is specific to RBG Law. The most effective index for your school consists of 50% LSAT score, 30% final UGPA, and 20% UGPA growth.

We created the API with the following in mind: Many law school admissions offices currently create an index that weights applicants' highest LSAT score and final UGPA. Some applicants, of course, will have entering credentials far enough above the median that we can presume they will be admitted. The opposite applies to the applicants with far lower entering credentials. The API is a tool that can be used to admit students who fall in the "gray area" between those two groups: the presumptively admitted and rejected students.

To apply the API at RBG Law, first calculate UGPA growth as the difference between students' final and first year UGPA. Then, multiply students' LSAT scores by 0.50, final UGPA by 0.30, and UGPA growth by 0.20. Add these three values together, and then transform these values into *z*-scores, which have a mean of 0 and a standard deviation of 1. This final step will indicate how far above or below the mean students fall in terms of their academic potential. Alternatively, we have included an Excel worksheet that is prepopulated with formulas to calculate the API. To use it, add an identifier for each applicant, as well as their first-semester UGPA, final UGPA, and highest LSAT score to Columns A through D. A value for UGPA growth and the API will populate based on the rules we describe above.

SUMMARY 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:

- All LGPA measures – 1S LGPA, 1L LGPA, final LGPA, and LGPA growth – are strong predictors of first-time bar performance.
- LGPA improvement from first semester to the end of law school is important for increasing a student's odds of bar passage.
- LGPA in all doctrinal bar courses as well as in the specific upper-level courses we studied (i.e., Article 9, Business Associations, Conflict of Laws, Criminal Procedure, Evidence, Family Law, and Trusts and Estates) are important indicators of bar success.
- Completing additional externship credits improves the probability of first-time bar passage among students with average or above average 1L class rank. Students with below average 1L class rank also benefit from completing additional skills-based courses.
- While LSAT score and final UGPA are important indicators of early law school performance, all measures of LGPA have a substantially stronger impact on bar passage odds than typical preadmission factors.
- UGPA growth predicts early law school performance as well as LSAT score and UGPA, and results in fewer racial disparities.

Based on these findings, we propose the following recommendations at RBG Law:

Properly contextualize preadmission factors when making admissions decisions. Our results demonstrate that LSAT score and UGPA are positively related to 1L LGPA. However, these preadmission factors should not be considered determinative of bar success. In fact, LSAT score and UGPA become less predictive of academic performance and bar passage over time and are weaker predictors of bar performance than all measures of LGPA. This suggests that although LSAT score and UGPA are relevant, they are not determinative of success. What happens in law school matters.

Consider applying the Academic Potential Index (API) to assist with making admissions decisions. Our findings indicate that the use of the API rather than a traditional LSAT/UGPA index may result in admitting a more diverse, yet equally capable and credentialed class of students. We have provided the composition of an API that best fits the data from your school in the previous section, as well as a suggestion regarding how to use it. We encourage you to contact us at research@accesslex.org for guidance adjusting the weights given to each metric in the calculation based on your institution's priorities. For example, giving greater weight to UGPA growth to generate an even more racially diverse class.

Encourage students to complete additional coursework and externships, depending on their 1L class rank. Students in the bottom half of their class rankings may benefit from enrolling in an additional skills-based course rather than additional doctrinal courses or externships. Conversely, among students with higher class rankings, encouraging externships may improve their odds of passing the bar exam.

Track LGPA across each year of law school to identify which students would benefit from an academic intervention, using the provided LGPA benchmarks for bar success (see p. 14). 1S LGPA, 1L LGPA, final LGPA, and LGPA growth are all strong predictors of bar passage outcomes and can indicate which students would benefit from early academic support. Our findings demonstrate that RBG Law students with a 1S LGPA of 3.04 and a 1L LGPA of 3.02 have a 75 percent predicted probability of passing the bar exam on their first attempt. Targeting interventions toward students below these benchmarks is critical to help struggling students develop the necessary skills to succeed in law school and on the bar exam.

Encourage and support the development of a "growth mindset" among faculty, staff, and students. We find that students' ability to improve their LGPA from their first semester to final has a large impact on the odds of bar passage. Furthermore, predicting whether an applicant possesses a growth mindset may be something to consider among future law school applicants using their UGPA growth (see Recommendation 2 above).

METHODOLOGY

a. Data

As noted above, your institution provided student data for 1,037 students who matriculated in 2015–2020, 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*
- *Bar exam passage*
- *Bar exam date and jurisdiction*
- *Matriculation year*
- *Graduation Year*
- *Undergraduate institution*
- *UGPA*
- *LSAT score*
- *Race*
- *Gender*
- *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:

- To investigate 1L LGPA, we use students' highest LSAT score, final (cumulative) UGPA, and UGPA growth.
- To investigate bar passage, we use 1S LGPA, 1L LGPA, final LGPA, LGPA growth, course credit hours, individual course GPAs, LSAT score, and final UGPA.

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.

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 (measured at the point in which the student completed approximately 30 credit hours)
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 ▪ 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

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 decline. Our models include 1S LGPA, which allows us to examine the effect of LGPA growth while holding 1S LGPA constant.

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

TABLE 3

Description of the Coursework Variables Used in the Analyses

	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: ▪ Skills-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 "skills-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% 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.

APPENDIX

a. Summary Statistics

TABLE 4

Summary Statistics

	Obs.	Median	Mean (or %)	Standard Deviation	Min.	Max.
Race						
Black	90		9%			
Hispanic/Latino	137		13%			
Asian	129		12%			
White	681		66%			
Gender						
Female	573		55%			
Male	464		45%			
Age at Matriculation	1037	24	25.51	5.1	20	55
Transferred Out	29		3%			
Academic Attrition	41		4%			
Other Attrition	52		5%			
First-Time Bar Passage						
Pass	496		58%			
Fail	365		42%			
Preadmission Variables						
Highest LSAT Score	1037	149	149.01	5.38	137	173
Final UGPA	1037	3.20	3.18	0.43	1.85	4.00
UGPA Growth	1034	0.07	0.13	0.38	-1.37	1.79
LGPA						
First Semester	1024	2.78	2.76	0.58	0.46	4.00
First Year	1010	2.77	2.79	0.56	0.43	4.00
Final	908	3.08	3.10	0.39	1.87	3.99
Growth	908	0.25	0.27	0.31	-1.44	1.88

Doctrinal LGPA						
Article 9	501	3.33	3.17	0.67	1.00	4.00
Business Associations	804	3.00	3.01	0.67	0.67	4.00
Conflict of Laws	279	3.00	2.98	0.82	0.67	4.00
Criminal Procedure	824	3.00	2.93	0.63	1.00	4.00
Evidence	924	3.00	2.94	0.66	1.00	4.00
Family Law	511	3.33	3.15	0.71	0.00	4.00
Trusts and Estates	657	3.00	3.04	0.68	0.00	4.00
1L Doctrinal Courses	802	2.79	2.80	0.56	0.00	4.00
Upper-Level Doctrinal Courses	944	3.00	3.01	0.49	0.00	4.00
Other Doctrinal Courses	747	3.00	2.97	0.54	1.00	4.00
All Doctrinal Courses	996	2.95	2.93	0.50	0.51	4.00
Credit Hours						
Clinic-Based	363	8	8.46	2.06	3	15
Externships	588	6	7.05	2.92	3	15
Legal Writing	1029	9	8.34	2.25	3	16
Skills-Based	886	2	2.03	0.35	0	3
Upper-Level Doctrinal Courses	1029	9	9.59	4.53	0	22
Other Doctrinal Courses	956	2	2.03	0.74	1	3
All Doctrinal Courses	1037	45	44.33	8.28	12	75

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.

TABLE 5

List of Models Described in This Report

Section of Report	Outcome Variable	Predictors of Interest	Control Variables Included in Model
What predicts law school performance?	1L LGPA	Highest LSAT score Final UGPA	Race, gender, age at matriculation, UGI selectivity (admission rate), number of years to complete their undergraduate degree, and number of LSAT attempts
		UGPA growth	First year UGPA, race, age at matriculation, UGI selectivity (admission rate), and number of years to complete their undergraduate degree
What predicts first-time bar exam performance?	First-time bar exam performance (pass or fail)	1S LGPA	Highest LSAT score, final UGPA, age at matriculation, and year of first bar exam attempt
		1L LGPA	Highest LSAT score, final UGPA, age at matriculation, and year of first bar exam attempt
		Final LGPA	Highest LSAT score, final UGPA, age at matriculation, and year of first bar exam attempt
		LGPA growth	Highest LSAT score, final UGPA, age at matriculation, and year of first bar exam attempt
		All doctrinal course LGPA and credit hours models (both in aggregate and in individual courses)	Highest LSAT score, final UGPA, and year of first bar exam attempt

b. Regression Output Tables

TABLE 6

What Predicts Law School Performance?

	Outcome: 1L LGPA	
	Model 1: LSAT Score and UGPA	Model 2: UGPA Growth
LSAT Score	0.16 *** (0.02)	
Final UGPA	0.17 *** (0.02)	
UGPA Growth		0.16 *** (0.02)
First-year UGPA		0.25 *** (0.02)
UGPA Growth Given First-year UGPA		0.00 (0.01)
UG Selectivity	-0.01 (0.02)	-0.05 ** (0.02)
Age at Matriculation	-0.02 (0.02)	-0.02 (0.02)
Took the LSAT more than once	-0.11 *** (0.03)	
R^2	0.26	0.17
Adjusted R^2	0.26	0.16
Num. obs.	962	960

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; All continuous variables are reported as z-scores, with a mean of 0 and standard deviation of 1. Race is included as a control variable, but those results are omitted from this table (see the Control Variables section above).

TABLE 7

What Predicts First-Time Bar Passage? LGPA Models

	Outcome: First-Time Bar Result			
	1S LGPA Model	1L LGPA Model	Final LGPA Model	LGPA Growth Model
1S LGPA	1.56 *** (0.14)			2.84 *** (0.23)
1L LGPA		1.66 *** (0.15)		
Final LGPA			2.07 *** (0.15)	
LGPA Growth				1.25 *** (0.17)
LGPA Growth Given 1S LGPA				0.11 (0.10)
LSAT Score	0.48 *** (0.12)	0.43 *** (0.12)	0.40 *** (0.12)	0.40 ** (0.12)
Final UGPA	0.08 (0.10)	0.03 (0.10)	-0.03 (0.11)	-0.06 (0.11)
Age at Matriculation	-0.20 (0.10)	-0.19 (0.11)	-0.25 * (0.11)	-0.24 * (0.11)
Took the bar in 2019	0.37 (0.31)	0.44 (0.32)	0.16 (0.33)	0.26 (0.33)
Took the bar in 2020	1.27 *** (0.33)	1.29 *** (0.33)	1.18 *** (0.34)	1.24 *** (0.34)
Took the bar in 2021	0.59 * (0.30)	0.69 * (0.30)	0.35 (0.31)	0.44 (0.31)
Took the bar in 2022	-0.33 (0.30)	-0.32 (0.31)	-0.87 ** (0.31)	-0.73 * (0.32)
Took the bar in 2023	0.22 (0.29)	0.30 (0.29)	0.06 (0.31)	0.14 (0.31)
Took the bar in CA	0.38 (0.23)	0.42 (0.24)	0.23 (0.24)	0.23 (0.24)
Took the bar in NY	0.20 (0.28)	0.16 (0.28)	0.17 (0.28)	0.19 (0.29)
Took the bar in DC	0.08 (0.22)	0.05 (0.23)	-0.11 (0.23)	-0.10 (0.24)
AIC	878.44	860.88	836.00	825.61
BIC	940.29	922.73	897.84	896.96
Log Likelihood	-426.22	-417.44	-405.00	-397.80
Deviance	852.44	834.88	810.00	795.61
Num. obs.	861	861	860	860

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; All continuous variables are reported as z-scores, with a mean of 0 and standard deviation of 1. Race is included as a control variable, but those results are omitted from this table (see the Control Variables section above).

TABLE 8

What Predicts First-Time Bar Passage? Course LGPA Models

	Outcome: First-Time Bar Result								
	Model 1: All Doctrinal Courses	Model 2: 1L Doctrinal Courses	Model 3: Upper-Level Doctrinal Courses	Model 4: Other Doctrinal Courses	Model 5: Four Courses	Model 6: Article 9	Model 7: Conflict of Laws	Model 8: Family Law	Model 9: Trusts and Estates
Doctrinal LGPA (Overall)	2.16 *** (0.15)								
1L Required Doctrinal LGPA		1.48 *** (0.13)							
Upper-Level Doctrinal LGPA			1.49 *** (0.12)						
Other Doctrinal LGPA				1.27 *** (0.13)					
Article 9 LGPA						0.74 *** (0.12)			
Business Associations LGPA					0.66 *** (0.12)				
Conflict of Laws LGPA							0.48 ** (0.15)		
Criminal Procedure LGPA					0.28 * (0.11)				
Evidence LGPA					0.78 *** (0.12)				
Family Law LGPA								0.62 *** (0.11)	

	Outcome: First-Time Bar Result								
	Model 1: All Doctrinal Courses	Model 2: 1L Doctrinal Courses	Model 3: Upper-Level Doctrinal Courses	Model 4: Other Doctrinal Courses	Model 5: Four Courses	Model 6: Article 9	Model 7: Conflict of Laws	Model 8: Family Law	Model 9: Trusts and Estates
Trusts and Estates LGPA									0.86 *** (0.11)
Took the bar in 2019	0.19 (0.34)	0.36 (0.32)	0.07 (0.32)	0.05 (0.30)	0.16 (0.33)	0.06 (0.36)	0.68 (0.68)	0.04 (0.45)	0.02 (0.34)
Took the bar in 2020	1.14 ** (0.36)	1.21 *** (0.34)	0.91 ** (0.33)	1.12 *** (0.34)	0.46 (0.33)	0.96 * (0.41)	0.73 (0.59)	0.79 (0.43)	1.06 ** (0.39)
Took the bar in 2021	0.53 (0.32)	0.72 * (0.30)	0.29 (0.30)	0.87 (0.58)	-0.41 (0.39)	0.68 (0.40)	0.37 (0.49)	0.59 (0.41)	0.61 (0.34)
Took the bar in 2022	-1.14 ** (0.36)	-0.46 (0.91)	-0.60 * (0.30)	-0.45 (0.29)	-0.49 (0.31)	-0.45 (0.39)	-0.33 (0.51)	-0.58 (0.39)	-0.63 (0.32)
Took the bar in 2023	0.08 (0.33)	0.29 (0.30)	-0.13 (0.29)	0.22 (0.28)	-0.25 (0.30)	0.56 (0.36)	0.17 (0.48)	-0.26 (0.39)	-0.04 (0.31)
Took the bar in CA	0.45 (0.26)	0.52 * (0.26)	0.49 * (0.23)	0.61 * (0.26)	0.40 (0.26)	0.96 *** (0.29)	0.44 (0.38)	0.69 * (0.29)	0.50 * (0.26)
Took the bar in NY	0.39 (0.33)	0.11 (0.31)	0.19 (0.28)	0.27 (0.30)	0.18 (0.31)	-0.20 (0.34)	0.06 (0.47)	0.06 (0.34)	0.11 (0.30)
Took the bar in DC	0.05 (0.25)	-0.05 (0.25)	0.09 (0.22)	0.27 (0.24)	0.16 (0.24)	0.19 (0.28)	0.44 (0.36)	0.24 (0.26)	0.23 (0.24)
AIC	713.45	687.50	872.26	739.95	716.97	562.66	348.29	586.84	729.16
BIC	773.02	746.40	934.11	798.68	784.56	616.56	394.77	640.71	786.60
Log Likelihood	-342.97	-330.75	-423.13	-356.98	-343.48	-268.33	-161.14	-280.42	-351.58
Deviance	685.95	661.50	846.26	713.95	686.97	536.66	322.29	560.84	703.16
Num. obs.	811	686	861	677	669	467	264	466	613

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; All continuous variables are reported as z-scores, with a mean of 0 and standard deviation of 1. Race is included as a control variable, but those results are omitted from this table (see the Control Variables section above).

TABLE 9

What Predicts First-Time Bar Passage? Course Credit Hour Models

	Outcome: First-Time Bar Passage						
	Model 1: Doctrinal (Overall) Courses	Model 2: Upper-Level Doctrinal Courses	Model 3: Other Doctrinal Courses	Model 4: Clinic-Based Courses	Model 5: Externship Courses	Model 6: Legal Writing Courses	Model 7: Skills-Based Courses
Doctrinal Credit Hours (Overall)	-0.17 (0.10)						
Upper-Level Doctrinal Credit Hours		-0.26 ** (0.09)					
7-9 Other Doctrinal Credit Hours			0.14 (0.18)				
11 or More Other Doctrinal Credit Hours			-0.24 (0.15)				
Clinic-Based Credit Hours				0.03 (0.20)			
Externship Credit Hours					0.24 (0.12)		
Legal Writing Credit Hours						-0.17 (0.09)	
3 Skills-Based Credit Hours							0.30 (0.26)
Age at Matriculation	-0.16 (0.10)	-0.15 (0.11)	-0.16 (0.10)	-0.20 (0.16)	-0.15 (0.12)	-0.17 (0.10)	-0.17 (0.10)
Took the bar in 2019	0.60 (0.33)	0.57 (0.33)	0.59 (0.32)	0.62 (0.50)	0.76 (0.39)	0.53 (0.31)	0.83 * (0.34)
Took the bar in 2020	1.46 *** (0.34)	1.42 *** (0.35)	1.45 *** (0.34)	1.30 * (0.52)	1.66 *** (0.41)	1.39 *** (0.33)	1.69 *** (0.36)
Took the bar in 2021	1.09 *** (0.32)	1.12 *** (0.32)	0.97 ** (0.31)	1.32 ** (0.49)	1.40 *** (0.39)	0.93 ** (0.31)	1.29 *** (0.33)
Took the bar in 2022	0.04	-0.00	-0.07	0.07	0.23	-0.06	0.29

	Outcome: First-Time Bar Passage						
	Model 1: Doctrinal (Overall) Courses	Model 2: Upper-Level Doctrinal Courses	Model 3: Other Doctrinal Courses	Model 4: Clinic-Based Courses	Model 5: Externship Courses	Model 6: Legal Writing Courses	Model 7: Skills-Based Courses
	(0.32)	(0.32)	(0.31)	(0.48)	(0.37)	(0.31)	(0.33)
Took the bar in 2023	0.97 **	1.02 **	0.88 **	0.92	1.52 ***	0.87 **	1.17 ***
	(0.31)	(0.31)	(0.30)	(0.47)	(0.38)	(0.30)	(0.34)
Took the bar in CA	0.47	0.47	0.43	0.61	0.00	0.47	0.44
	(0.24)	(0.25)	(0.24)	(0.38)	(0.31)	(0.24)	(0.25)
Took the bar in NY	0.21	0.17	0.21	0.87 *	-0.02	0.21	0.08
	(0.29)	(0.29)	(0.29)	(0.44)	(0.35)	(0.29)	(0.29)
Took the bar in DC	0.10	0.03	0.04	0.17	-0.24	0.08	0.04
	(0.23)	(0.24)	(0.23)	(0.38)	(0.30)	(0.23)	(0.23)
Doctrinal Credits Given 1L Rank	0.35 *** (0.10)						
Upper-Level Doctrinal Credits Given 1L Rank		0.54 *** (0.09)					
7-9 Other Doctrinal Credits Given 1L Rank			0.36 (0.21)				
11 or More Other Doctrinal Credits Given 1L Rank			0.02 (0.18)				
Clinic-Based Credits Given 1L Rank				-0.06 (0.20)			
Externship Credits Given 1L Rank					-0.26 (0.14)		
Legal Writing Credits Given 1L Rank						0.04 (0.10)	
3 Skills-Based Credits Given 1L Rank							0.03 (0.31)
AIC	823.62	793.22	832.47	356.37	545.08	831.71	818.05
BIC	899.26	868.86	917.57	417.40	614.21	907.35	902.64
Log Likelihood	-395.81	-380.61	-398.24	-162.18	-256.54	-399.86	-391.03
Deviance	791.62	761.22	796.47	324.37	513.08	799.71	782.05

	Outcome: First-Time Bar Passage						
	Model 1: Doctrinal (Overall) Courses	Model 2: Upper-Level Doctrinal Courses	Model 3: Other Doctrinal Courses	Model 4: Clinic-Based Courses	Model 5: Externship Courses	Model 6: Legal Writing Courses	Model 7: Skills-Based Courses
Num. obs.	835	835	835	335	556	835	812

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; All continuous variables are reported as z-scores, with a mean of 0 and standard deviation of 1. Race is included as a control variable, but those results are omitted from this table (see the Control Variables section above).

c. Interpreting Linear Regression

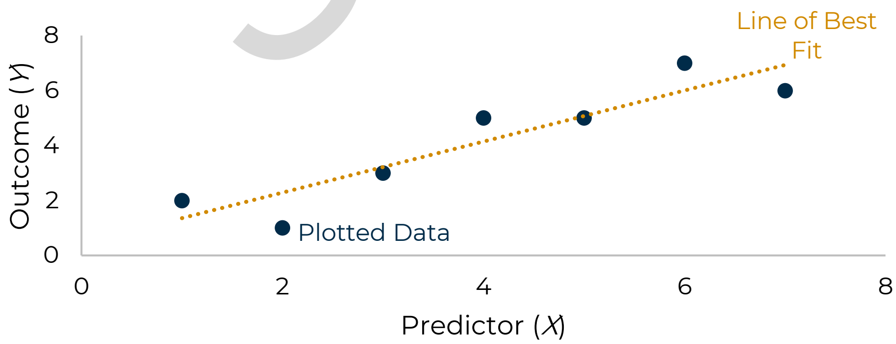
Ordinary least squares (OLS) regression, often referred to simply as "linear regression," estimates the relationship between at least one independent variable (predictor) and one dependent variable (outcome), the latter being distributed continuously (i.e., taking on any value, including negative values) or, in many cases, discretely (i.e., taking on only a finite number of values). As noted above, the outcomes 1S LGPA, 1L LGPA, and final LGPA 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 9

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, 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.

d. Interpreting Logistic Regression

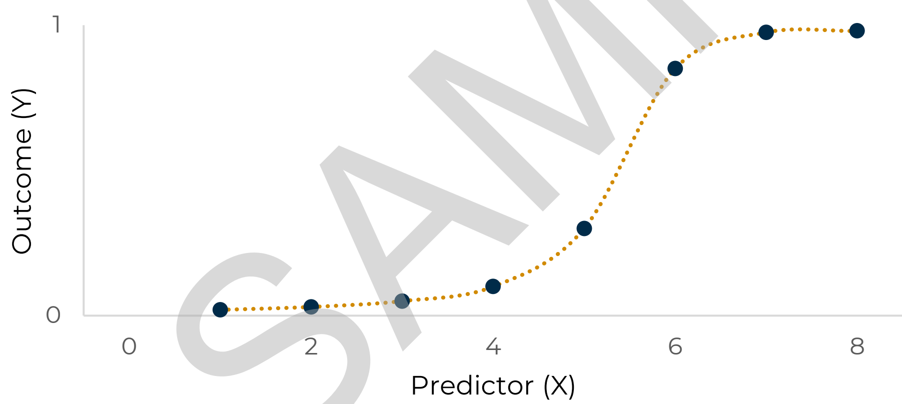
Logistic regression estimates the relationship between at least one independent variable (predictor) and one categorical dependent variable (outcome), the latter being a variable with a limited number of possible values. For these analyses, we focus exclusively on a specific form of logistic regression 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.

FIGURE 10

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 etermination as to whether the effect is practically significant

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*.

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.

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.

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