Measuring "Up": The Promise of Undergraduate GPA Growth in Law School Admissions

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ABSTRACT

Law school admissions emphasize Law School Admission Test (LSAT) scores and final undergraduate GPA (UGPA) despite these measures' racial and ethnic scoring disparities. Using a sample of 5,599 recent law school students from 14 law schools, we compare the predictive power of UGPA growth to that of final UGPA and LSAT scores in law school admissions. We find that UGPA growth is positively associated with first-year law school GPA (1L LGPA) and negatively associated with first-year (1L) non-transfer attrition. Furthermore, our findings indicate that, unlike final UGPA and LSAT scores, UGPA growth does not substantively vary by race/ethnicity. UGPA growth might be a viable metric to consider as law schools examine how to recruit diverse cohorts without considering race.

Keywords: diversity, growth mindset, law school, admissions

INTRODUCTION

Every year, millions of hopeful students apply to selective colleges, universities, and graduate and professional schools in the United States, vying for a limited number of available seats at the table of educational opportunity (National Center for Education Statistics, 2021; Urban Institute, 2024). Admissions officers at these institutions face the herculean task of assessing the merit, potential, and deservingness of each applicant — concepts already fraught with controversy and confusion — to decide who to admit and who to exclude. The sheer volume of these decisions is prodigious. According to the Integrated Postsecondary Education Data System (IPEDS) admission and enrollment data in the Urban Institute Education Data Portal, colleges received 12,235,901 applications in 2021 — averaging over 6,000 applications per school. According to the latest data from the American Bar Association (2023), the 196 nationally accredited law schools in the United States received a total of 413,928 applications for the 2022–2023 academic year, with a median number of applications per school over 1,400.

The American Bar Association's (ABA) Standard 501, which requires that "a law school shall only admit applicants who appear capable of satisfactorily completing its program of legal education and being admitted to the bar" (ABA, 2018), intensifies the pressure on law schools to select promising applicants, in addition to competing institutional priorities such as law school rankings and diversity commitments.

The volume of applications these institutions receive — and the conflicting interests they must balance — further constrict limited time and personnel resources. Therefore, colleges, universities, graduate schools, and professional schools wield various quantitative tools to sift through their applications as efficiently as possible.

Law school admissions committees typically assign the heaviest weight in admissions determinations to two factors: the Law School Admission Test (LSAT) score and final cumulative undergraduate GPA (UGPA) (Taylor, 2018). But these traditional measures tend to benefit students of higher socioeconomic means and greater cultural capital, possibly because these students have more time, financial resources, support, and background knowledge regarding the application and testing process (Shultz & Zedeck, 2012; Taylor & Christensen, 2017; Taylor, 2018, 2019; Rosales & Walker, 2021).

Given the Supreme Court's recent decision in *Students for Fair Admissions v. Harvard* (2023), law schools may now only pursue race-neutral methods to diversify their classes — a still-worthwhile endeavor considering the racially disparate outcomes associated with final UGPA and LSAT score. As law schools search for objective and equitable supplements to these metrics, we offer one suggestion that is easily calculable and already collected and considered among law school admissions offices: the change in an applicant's UGPA from the first year to the final year ("UGPA growth") which may capture non-cognitive student aptitudes and non-traditional notions of merit — namely, student growth mindset.

To that end, we examine to what extent does:

- UGPA growth predict first-year (1L) law school GPA (LGPA) and 1L attrition?
- The magnitude of UGPA growth's effect on the above outcomes compare to those of final UGPA and LSAT score?
- UGPA growth vary by race or ethnicity — both absolutely and relative to final UGPA and LSAT score?

We then consider how schools might operationalize and integrate UGPA growth measures into their admissions procedures, through the creation of an academic potential indicator index, as well as what this might mean for efforts to diversify campus student bodies.

LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

Background

The American Bar Association requires that law schools (1) use a valid and reliable admissions test, per Standard 503, and (2) only admit students who seem capable of completing the J.D. program of study and passing the bar exam, per Standard 501 (American Bar Association, 2018). Admissions officers typically make these determinations using the information available in each applicant's report from the Law School Admission Council (LSAC), which contains their Law School Admission Test (LSAT) scores and postsecondary transcripts, including final UGPA.

Law schools often combine UGPA and LSAT scores into a single index score for each applicant. The relative weights of UGPA and LSAT score within this index vary by school, and so does the weight of the index itself relevant to other application factors (LSAC, accessed 2024). Although law schools seldom share specific details about their admissions calculus, circumstantial evidence suggests that most law schools rely particularly heavily on LSAT scores in shaping their entering classes. For example, according to LSAC's (2021) National Profile of law school applications in 2020, after aggregating across UGPA values, a jump from the 140–144 LSAT scoring band to the 145–149 band was associated with a 40-percentage-point increase in admission rate. Jumping from the 145–149 band to the 150–159 band added another 19 percentage points to the aggregate admission rate. Clearly, minor differences in LSAT score correspond to disproportionate swings in an applicant's probability of admission.

It is worth noting, too, that in addition to institutional objectives regarding accreditation and student-body diversity, law schools have also juggled the competing goal of maneuvering upward in rankings. The latest *U.S. News & World Report Best Law School Rankings* weight law school selectivity factors as 10% of a law school's ranking score. Selectivity factors include acceptance rate (one percent), median LSAT and Graduate Record Examination (GRE) score (five percent), and final UGPA (four percent) (Morse, 2023). However, law schools may face slightly less pressure to improve their rankings in the wake of the recent rankings boycott, in which over 40 top-ranked law schools publicly announced they would no longer supply data to *U.S. News & World Report* (Graham, 2023).

LSAT and GRE Pose Racial Inequities

Despite the reliance on LSAT scores in law school admissions, researchers have questioned the biases and relative predictive validity associated with high-stakes standardized testing across higher education. This research spans admission to undergraduate, graduate, and professional programs, often focusing on the SAT, ACT, or GRE, and suggests that these assessments tend to capture and perpetuate racial inequities, despite sometimes offering limited or variable payoff in predicting academic performance (Cunningham-Williams et al., 2018; Fina et al., 2018; Fleming & Garcia, 1998; Geiser & Studley, 2002; Kobrin & Patterson, 2011; Zwick & Himelfarb, 2011).

Similarly, the LSAT has historically yielded differential test results according to race, with Black test-takers scoring, on average, 11 points lower than White and Asian takers in the 2016–17 admission cycle. Given these score disparities, it is unsurprising that, as Taylor (2019) reports, 49% of Black applicants are shut out from admission to any law school. This suggests that the test may reward student characteristics other than merit; for example, cultural capital and student ability to invest time and fees into test preparation, which tend to vary by race and ethnicity (Geiser, 2017).

Even for admitted students, heavy emphasis on LSAT score and final UGPA contributes to inequities due to related scholarship policies. Taylor and Christensen (2017) and Taylor (2018) observe that, in 2016, White law students received merit scholarships at starkly higher rates than Black and Hispanic law students — with differences of 18 percentage points and 15 percentage points, respectively. Additionally, merit scholarships constituted most (79%) of the gift aid awarded in law school. In 2016, Law School Survey of Student Engagement (LSSSE) respondents who reported higher LSAT scores also reported higher rates of merit scholarships. These trends imply a system where students with lower LSAT and UGPA credentials effectively subsidize the tuition of their higher-scoring peers. Given the wide racial disparities in LSAT results reported by Taylor (2018), the lower-scoring group likely contains a larger proportion of students of color than the higher-scoring group as well. This predicament calls for an easily obtainable supplementary admission measure — based on a different conceptualization of merit — that can match the predictive power of LSAT score and UGPA.

The Changing Admissions Landscape

In the wake of *Students for Fair Admissions v. Harvard* (2023), it has become, and will continue to be, increasingly important for institutions of higher education to carefully reconsider any components of their admissions policies that distribute disproportionate outcomes according to race. Although the recent Supreme Court decision is expected to diminish diversity in higher education and law schools by curbing the consideration of race in admissions, it could prompt admissions offices to reckon with the contradictions inherent in the heavy use of standardized test scores (Scott et al., 2023a). Justice Clarence Thomas highlights this contradiction in his concurrence and dissent in *Grutter v. Bollinger* (2003), noting that Columbia University first introduced intelligence tests in the early twentieth century — "with full knowledge of their disparate impact" — as a tool to admit fewer Jewish applicants. Justice Thomas goes on to assert that "no modern law school can claim ignorance of the poor performance of blacks relatively speaking, on the [LSAT]" (p. 22).

Recognizing the tradeoffs associated with the LSAT, some stakeholders have advocated for the American Bar Association to relax its Standard 503 (ABA, 2018; Sloan, 2022). This has led many law schools to accept alternative tests, like the GRE in lieu of LSAT scores in recent years. However, in the 2020–2021 admissions cycle, applicants submitting alternative test scores remained a small minority, comprising just 50 students nationally and less than one percent of first-year enrollees overall (ABA, 2021). Furthermore, Roberts et al. (2021) observe that even the GRE correlates "more strongly with race, gender, and socioeconomic status than performance metrics" in a literature review analyzing STEM doctoral programs. In fact, Francis et al.'s (2022) systematic review of graduate programs in health professions suggests that deemphasizing the GRE in admissions has improved the racial and ethnic diversity of entering classes.

Meanwhile, Shultz and Zedeck (2012) suggest supplementing LSAT score and final UGPA with other, non-cognitive measures of professional competence to achieve a more complete picture of law school readiness and advance diversity in the legal academy and profession.

Other universities, graduate schools, and professional schools have already begun shifting toward a holistic review approach (Hossler et al., 2019, Francis et al., 2022). This change is particularly evident in the health professions, and typically involves increased consideration of nonacademic or personality characteristics, personal experiences, and background in addition to traditional academic factors (Francis et al., 2022; Maude & Kirby, 2022). Holistic review considers the "whole file, whole person, and whole context," and has been linked to more diverse entering classes (Maude & Kirby, 2022, p. 76). However, it requires more time, personnel, and resources than traditional application review due to its emphasis on factors beyond test scores. Rosinger et al. (2021) note that emphasizing academic rigor over test scores may improve access for underrepresented racial and ethnic groups, identifying an avenue for future research that we seek to address, in part, with this work.

In February 2023, ABA President Paulette Brown voiced her concern that the elimination of standardized testing requirements could open the door for other injustices, a sentiment echoed by Howard Law dean Danielle R. Holley, who worried "recommendation letters, and other types of packaging that rely on students having both information and privilege, will become the currency of the realm, instead of a more objective factor like LSAT" (Fortin, 2023). That month, the ABA House of Delegates rejected a proposal to eliminate its Standard 503, which mandates that member schools require applicants to submit scores earned from taking valid and reliable admissions tests (Sloan, 2023). Any proposed alternative to the LSAT should be ostensibly reliable or quantitative in nature to achieve external validity.

The JD-Next Program is one recently validated law-school admissions metric that may help mitigate racial bias in traditional admissions metrics. The program consists of a short course of introductory 1L curriculum and study strategies, culminating in a JD-Next exam, and is intended to measure student potential for learning and growth (Findley et al., 2023). Preliminary research suggests that JD-Next may be valid, reliable, and less prone to racial and ethnic disparities than LSAT score. As of January 2024, approximately 50 law schools have received variances to use JD-Next in admissions (ABA, 2024). This implies a broad appetite for new quantitative law school admissions measures.

Academic Momentum

The use of final UGPA in admissions may also penalize students for delayed academic momentum. Academic momentum literature emphasizes the importance of early wins in college to propel students toward higher grades and program completion (Adelman, 1999, 2006). For example, students who enter college with Advanced Placement or Dual Enrollment credits, summer school experience, or higher starting credit-loads have been observed to complete their bachelor's or associate degrees more reliably (Chan & Wang, 2018; Martin et al., 2013, Wang et al., 2015). First-year UGPA is often treated as an indicator of academic momentum (Chan & Wang, 2018).

Not all students, however, come to college equally equipped for immediate success. Several reports suggest that students from families of lower socioeconomic status and students of color are less prepared for college than their peers (e.g., Cabrera et al., 2006; Reber & Smith, 2023; *Where We Want to Go…*, 2006). This gap in preparedness may explain the lower first-year persistence rates Perez and Harris-Wilkerson (2021) report among Black and Hispanic undergraduate students.

These trends may contribute to differences in academic momentum. For example, Chan and Wang (2018) find that high school preparation, financial support, and family and peer support may be associated with academic momentum. Clovis and Chang (2021) find that varying levels of these supports may lead to observed differences in momentum indicators by race. These findings are consistent with Engberg and Wolniak's (2010) conclusions that high school infrastructure and exposure to school violence "affect first-year college grades above and beyond precollege academic achievement" (p. 451). The researchers find that Black and Hispanic students and students with a household income less than or equal to $50,000 per year achieved lower first-year college grades than White students.

Students with fewer resources or without family members who attended college may need an extra semester or two to develop academic momentum through college-level study strategies, time management, and course skills (Bowman & Levtov, 2020). Indeed, Martin et al.'s (2013) study of academic momentum predictors during the first four semesters of college reveals that (1) high school achievement predicts early college achievement but becomes less predictive over time, and (2) although each semester beyond the first semester is significantly predicted by all preceding semesters, the betas diminish sharply as the temporal distance between semesters increases. For example, Martin et al. finds that first-semester UGPA predicts second-semester UGPA with a beta of 0.35 and $p < 0.001$, but its effects on third- and fourth-semester UGPA are diminished by two-thirds and four-fifths, respectively. This suggests that, while past grades can predict future grades, there is room for students to grow and exert their own influence.

Growth Mindset and Delayed Academic Momentum

One such avenue by which students might achieve this growth is through changes in non-cognitive skills like conscientiousness, grit, growth mindset, persistence, resilience, and self-efficacy. A sizable body of literature has proposed positive relationships between these factors and academic and professional outcomes, from primary school through graduate and professional school, and to the workforce (Audley & Donaldson, 2022; Duckworth, 2007; Dweck, 2006, 2017; Hamilton, 2022; Hu et al., 2011; Maude & Kirby, 2022; Sedlacek, 2003; Sellon et al., 2023, Yalcin & Yilmaz, 2023).

Examining the relationship between growth mindset interventions and college grades, Akos et al. (2022) and Broda et al. (2018) find positive relationships, particularly in student groups facing a persistent GPA gap. Aditomo (2015) observes that, among a sample of Indonesian second-semester college students, a growth mindset toward academic performance is associated with better recovery from academic setbacks in a statistics course. Miller and Srougi (2021) similarly report higher grades associated with a growth mindset intervention among American college students taking a biochemistry course. Meanwhile, Hu et al. (2011) associate student growth with college persistence, and Fink et al. (2023) report positive test score outcomes associated with a growth mindset intervention in nontraditional community college students. Although the literature generally suggests that growth mindset holds promise for improving student outcomes (Burnette et al., 2022), not all studies find meaningful relationships between growth mindset and grades or completion (e.g., Brez et al., 2020; Elinich et al., 2023), and Macnamara & Burgoyne (2023) argue that growth mindset studies often suffer from poor design, analysis, and reporting.

Dweck (2006) defines a growth mindset as the belief that “basic qualities are things you can cultivate through your efforts, your strategies, and help from others” (p. 7). Importantly, if a student possesses this belief, skills, knowledge, and outcomes can be improved (Bowman & Levtov, 2020; Dweck & Leggett, 1998). To the extent that academic momentum represents another outcome, it too can be assumed to be malleable. Thus, growth mindset theory might support a framework for a concept of *delayed* academic momentum.

Much of the research on academic momentum has emphasized the importance of establishing momentum within a student’s first year (e.g., Adelman 1999, 2006; Chan & Wang, 2018; Martin et al., 2013, Wang et al., 2015). Although maintaining momentum is easier following a strong start, growth mindset theory would suggest that momentum is not necessarily fixed and might be generated following initial struggles via changes in behaviors, effort, and strategies.

However, focusing on a cumulative final grade point average masks this growth. A student with a lower first-semester or first-year UGPA may finish with a lower final UGPA than their peers, despite marked improvement and stellar performance in their second, third, and fourth years. For example, the highest cumulative UGPA a hypothetical student with first-year undergraduate grade point average of 2.0 (on a four-point scale) can achieve is a 3.5, assuming the student earns perfect grades for the remainder of their undergraduate studies.

The hypothetical student's final cumulative GPA of 3.5 would place them below the median UGPA value for the entering classes of most (122 out of 196) ABA-approved law schools (ABA, 2022). This reality may leave the student with fewer options for their choice of law school and their competitiveness for financial aid awards.

Therefore, by relying on a static UGPA in admissions, law schools may inadvertently penalize applicants for their lack of high school preparation and financial, family, or peer support upon entering college. Moreover, the use of this static measure overlooks the malleability of student development and the possibility of delayed academic momentum following a less-than-ideal start. A dynamic measure accounting for change over time may prove a better assessment of student aptitude than a final UGPA measure collected at a single point in time. Guidance from the LSAC supports this argument, advising that law schools supplement final UGPA with other considerations including "the applicant's performance from year to year" in college (LSAC, 2014).

Measuring Student Growth

Researchers have taken several different approaches to operationalizing student growth. Past studies have used assessments, portfolios, and rubrics to measure student growth, as well as local and national surveys like the National Survey of Student Engagement (NSSE), for undergraduate students. Much of the available student growth literature relies on self-reporting via subjective survey instruments. Bowman (2013), however, observes low correlations between "longitudinal and self-reported gains on the same construct[s]," and concludes that "recent research has cast serious doubt upon the (seemingly reasonable) assumption that college students can accurately report their own growth" (p. 6). Bowman recommends against self-reporting altogether and instead suggests using longitudinal assessments of cognitive outcomes, pre-tests and post-tests, standardized examinations, and other performance measures.

Bell-Ellwanger (2019) and Ehlert et al. (2014) offer several performance-based strategies to measure student growth. Most of these measures of growth, existing in the context of college instructional evaluation, place the onus to change upon the instructor. These approaches include value-added modeling (to help convey the school's contribution to student growth); student growth percentile ("whether or not a student does better than his or her peers"); and gain score measures, which assess "year-over-year changes in scores from a comparable assessment" (Bell-Ellwanger, 2019, pp. 22–23).

Since our conceptual framework links momentum — particularly delayed momentum — with growth mindset, it bears repeating that first-year UGPA has been acknowledged as an indicator of early momentum (Chan & Wang, 2018). This suggests that later improvements in UGPA may represent gains in momentum. Hu et al. (2011) similarly find that first-year UGPA predicts persistence better than self-reported student growth or score differences on pre- and post-tests.

Taylor et al. (2021) use a growth measurement approach resembling that of the gain score and UGPA measures described above: the difference between final law school GPA (LGPA) and first-semester LGPA. One key difference from the growth measures illuminated by Bell-Ellwanger (2019) and Ehlert et al. (2014), however, is that Taylor et al.'s approach places theoretical responsibility for observed growth on the student.

Taylor et al. (2021) find that the degree to which a law student improves their LGPA from the first semester to graduation can predict their probability of first-time bar passage about as well as final LGPA, and about five times as well as either LSAT or UGPA. The authors attribute this relationship, at least in part, to student growth mindset among those who achieved vast improvements in academic performance. Similarly, Marks and Moss (2016) find a positive relationship between upward UGPA trajectory and law school performance among recent law school graduates who achieved lower starting grades in college. The authors propose that this UGPA improvement may serve as a proxy for resilience.

We thus theorize that students who accumulate compensatory academic momentum by substantially improving their undergraduate GPA between the first year of college and graduation are more likely to engage in growth mindset thinking and behaviors to accomplish this feat.

The 1L Transition

In turn, we believe the same personal characteristics that allow students to finish strong in college may portend positive outcomes in the first year of law school.

Law school, especially the first year, is notoriously difficult for even the best-prepared students. Capable law students often report needing to study more often and more efficiently than in college to keep up with course materials and other expectations. For many students, law school may be the first time they are confronted with the possibility that their approach to coursework needs improvement (Flanagan, 2014).

Flanagan (2014) argues that, in general, law students are increasingly underprepared for the rigors of law school. Christopher (2019) adds that law students often respond negatively to their struggles in law school, viewing the difficulties of the 1L year as failures rather than opportunities. She calls for legal educators to "convey to students that their struggle is normal. In fact, struggle is productive — learning is hard, and lawyers learn and struggle throughout their careers" (p. 1). In her exploration of minority attrition rates in law school, Robbins (2019) attributes some responsibility for higher minority attrition rates to both stereotype threat and a lack of insider knowledge about law school, emphasizing that "transparency about expectations, methodology, and assessments is critical to the success of law students, particularly those who do not have support networks with lawyers who have gone through the process and are able to guide them along the way." Flanagan, Christopher, and Robbins recommend study skills interventions, attitude interventions, formative assessments, and increased academic support to mitigate skills gaps and other bumps in the 1L transition.

The nature of the difficulties 1L students face, as well as the commonly prescribed solutions to these difficulties, suggest that incoming students who have already demonstrated growth in their undergraduate studies may possess non-cognitive advantages when it comes to mindset, study skills, and work ethic. These are students who have already learned how to build academic momentum despite setbacks.

We therefore hypothesize that UGPA growth will predict positive law school outcomes (first-year GPA, attrition, final GPA, and bar passage) and may prove a useful criterion for law school admissions staff. If UGPA growth indeed predicts positive law school outcomes — particularly 1L LGPA and 1L attrition — and imposes fewer racial and ethnic disparities, we theorize that it could be a particularly promising tool for maintaining diverse entering law school classes — a consideration of heightened significance in the wake of *Students for Fair Admissions v. Harvard*.

DATA AND METHODS

Sample

We derive our sample from institutional partnerships with 14 law schools. Our sample includes UGPA growth data for 5,599 students who matriculated to one of those partner law schools across 11 graduating classes, from 2012 to 2021. The data set contains student demographic data including race, age, and gender; preadmission factors such as undergraduate GPA, LSAT score, undergraduate transfer, and years to complete undergraduate study; and law school outcomes data such as 1L attrition, 1L LGPA, and first-time bar passage. Every observation in the overall sample contains, at minimum, a first-year and final UGPA, which we use to estimate UGPA growth. However, there is some variation in data reporting by school along our outcome variables of interest — particularly 1L attrition and first-time bar passage.

In this section, we describe the overall sample, but each of our models ultimately comprises a subset of this sample depending on the availability of the outcome variable. Where possible, we also match participants' undergraduate institutions to acceptance rates from IPEDS.

Sample Characteristics

Table 1 details the descriptive statistics for our sample as well as the population of ABA-approved law schools during the study period.

TABLE 1

Sample Characteristics

Variable/Level	Sample *n*	*%*	*Mean*	Population *N*	*%*	*Mean*
Final UGPA*	5,623	-	3.32	-	-	3.43
LSAT Score*	5,421	-	154.1	-	-	156
First-Time Bar Passage: Fail*	775	21.9	-	44,925	18.4	-
First-Time Bar Passage: Pass*	2,765	78.1	-	198,641	81.6	-
Race: Asian*	278	5.6	-	23,123	6.8	-
Race: Black*	376	7.5	-	30,855	9.0	-
Race: Hispanic*	350	7.0	-	45,065	13.2	-
Race: Multiracial*	124	2.5	-	12,794	3.7	-
Race: White*	3,530	70.6	-	196,089	57.3	-
Race: Remaining*	67	1.3	-	13,315	3.9	-
Race: Unknown	273	5.5	-	15,286	4.5	-
Gender: Female*	2,869	51.1	-	109,487	54.6	-
Gender: Male*	2,741	48.9	-	91,208	45.4	-
1L Non-transfer attrition: Yes	221	6.0	-	22,617	6.3	-
1L Non-transfer attrition: No	3,472	94.0	-	334,768	93.7	-

*Differences between sample and population are statistically significant ($p < 0.05$).

The sample is reasonably — but imperfectly — representative of the population of law school students during the sample period. Even where the sample's bar passage rate, LSAT score, race, and gender composition differ from the population to a statistically significant degree, the differences remain small. However, two of the variables deviate more notably from the population than the others in the sample.

Firstly, our sample overrepresents White students by an estimated 13 percentage points and underrepresents Hispanic students by approximately six percentage points ($p < 0.001$). Students in our “remaining” category, whose counts are too few to disaggregate in modeling, also appear in our sample at a higher rate than the population ($p < 0.001$). This group consists of students identifying as American Indian or Alaska Native, Native Hawaiian or Pacific Islander, and non-U.S. citizens.

Secondly, the average final UGPA in the sample falls below the typical median UGPA in the population during that time: 3.32 compared to 3.43 ($p < 0.001$).

Overall, while we believe our sample is generally representative of the population, our findings may be less generalizable to Hispanic, American Indian or Alaska Native, Native Hawaiian or Pacific Islander, and non-U.S. citizen students.

Measures and Materials

Prior to analysis, we z-standardize all continuous covariates around the dataset’s grand mean to compare effect sizes on a common scale. See Table A.1 for descriptive statistics on the raw variables of interest.

Predictor Variables

Our predictor variable of interest is UGPA growth, defined as the difference between final UGPA and first-year UGPA.

We also model final UGPA and LSAT score as predictors of our outcome variables for comparison. As we discussed in the literature review above, law schools rely heavily on final UGPA and LSAT scores to guide admissions decisions. Therefore, the utility of UGPA growth depends, in part, on its predictive validity and equity relative to these traditional preadmission factors. Since some students submit multiple LSAT scores, we consider the highest reported score for each student. This approach reflects that of most law school admissions offices (Kuris, 2022; Lauth et al., 2014).

Outcome Variables

We model two outcome variables for analysis: (1) 1L LGPA and (2) 1L attrition (i.e., withdrawal from law school) not attributable to transfer to another law school (hereafter "1L non-transfer attrition"). Two law schools in our sample report raw 1L LGPA values on a scale other than the typical 0.0–4.0 scale (with values up to 4.33 possible). For presentation of summary statistics, we convert 1L LGPA for students attending these schools to a 0–4.0 scale prior to calculating z-scores for 1L LGPA. First-year (1L) non-transfer attrition is binary, taking values of *yes* or *no*.

We select these measures given their relevance to other traditional admissions metrics, like LSAT score, which LSAC designed to predict 1L academic performance. Therefore, predictions of early law school outcomes provide useful comparisons between UGPA growth and traditional preadmission metrics. 1L LGPA and 1L non-transfer attrition also bear relevance for law schools' compliance with ABA Standard 501, which mandates that law schools admit students capable of satisfactorily completing their program of legal education. Since most non-transfer attrition occurs in the first year of law school, preventing 1L non-transfer attrition represents a critical objective at any institution (ABA, 2018).

We elect not to analyze outcomes further removed from the 1L year, like first-time bar passage, final LGPA, or upper-level attrition for several reasons. Firstly, there is a substantial temporal lag (approximately four years, on average) between these bar exam outcomes and our preadmission factors of interest. Secondly, the use of LSAT scores to predict bar outcomes is explicitly contrary to the guidance published by the test's creators, LSAC. Lastly, initial findings from a separate research project suggest that the relationships previously reported in legal education research (e.g., Georgakopoulos et al., 2013; Taylor et al., 2021) between bar passage and LSAT score and final UGPA are, in fact, mediated by an individual's law school GPA (Scott et al., 2024).

Control Variables

We consider several control variables related to student demographic characteristics and academic history, including age, race, gender, year, law school, undergraduate transfer, years to complete college, and undergraduate selectivity. Where we include law school effects, we anonymize the institutions in this report. We also include first-year UGPA as a control variable in each model to account for students' starting places.

First-year UGPA is the grade point average a student attained after completing either their first two semesters of undergraduate studies or earning approximately 30 credit hours, depending on which definition a school used. This designation is made regardless of a student's enrollment type (i.e., part-time versus full-time) and whether the student transferred to another undergraduate institution either within their first year or later (e.g., a student enrolls in community college for their first year or two and then transfers to a four-year school). To address these sources of possible systematic variation, in model building, we consider as control variables the number of years a student took to complete their undergraduate studies, a student's undergraduate enrollment type, and whether the student transferred undergraduate institutions. In addition, we assess the extent to which our results change when we restrict our sample to students who completed their studies in four years, did not transfer undergraduate institutions, or met both criteria.

Analytic Plan

We attempt to account for the best model fit, the theoretical considerations that we discuss in our literature review, and the nested structure of our data within individual law schools. To do so, we first examine the bivariate relationships between our predictor, mediator, and outcome variables and their relationships with our potential control variables. Those control variables that are related to either the predictor and the outcome or the predictor and the mediator are considered viable control variables.

Our data is nested within schools, and we examine the intraclass correlations (ICC) of our outcome variables to determine at what level the variance lies — either within or between schools. The ICCs for 1L LGPA and 1L non-transfer attrition are 0.19 and 0.18, indicating that more than 80% of the variation in our outcomes lies within schools. Since most variation in these outcomes occurs within schools, we take a fixed effects regression approach using the "*fixest*" package for *R*, applying fixed effects for both school and matriculation year (Bergé, 2018). This allows us to focus on the extent to which UGPA growth predicts 1L LGPA and attrition on average, regardless of the specific school or matriculation year. This approach allows us to condition out the variance in our outcomes that is attributable to school-specific, time invariant factors — both observed and unobserved.

We use ordinary least squares (OLS) regression for our models predicting 1L LGPA, and binomial logistic regression for our models predicting 1L non-transfer attrition. For each outcome, we fit three models: our null model, which includes only UGPA growth and first-year UGPA; a maximal model that includes all control variables; and our preferred model that includes only those control variables that improve model fit, as measured by Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), R^2, and pseudo-R^2. Finally, following model selection, we check that regression assumptions are met before finalizing our models.

To compare variation in UGPA growth, LSAT score, and final UGPA by race/ethnicity, we graphically plot the distributions of each indicator. This enables us to compare measures of center as well as the spread of values across the distribution.

Lastly, to make these results practicable, we develop an academic potential index (API), one possible avenue by which schools might integrate and operationalize UGPA growth in the admissions process alongside (rather than in place of) LSAT score and final UGPA. We derive the API as a combination of LSAT score, final UGPA, and UGPA growth that best explains variation in 1L LGPA and reduces racial disparities, while also being simple to use and easy to calculate. For comparison, we calculate what we consider to be a reasonable approximation of a typical LSAT-UGPA index (LUI), weighting these indicators based on insight we have gleaned in discussions with law school deans, faculty, and admissions staff.

We then simulate a scenario in which the API might be used in admissions to predict 1L LGPA. We compare the explanatory power of both indices as well as the racial composition of those students who would be admitted by using the LUI to those using the API.

RESULTS

As described above, we fit two primary models, one that conditions 1L LGPA on UGPA growth and another that treats 1L non-transfer attrition as a function of UGPA growth. We then fit two additional models that condition our outcomes on both LSAT score and final UGPA, using the results obtained from these models to draw comparisons with those obtained from our UGPA growth models.

1L LGPA

Our preferred model predicting 1L LGPA as a function of UGPA growth includes students' first-year cumulative UGPA (to account for student's starting place), undergraduate admission rate (a proxy for institutional selectivity), race, and gender. (Neither undergraduate transfer status nor years to complete college improved model fit and are therefore excluded from our preferred model.)

We find that UGPA growth has a positive and statistically significant relationship with 1L LGPA ($\beta = 0.25$; $p < .001$). Since our outcomes and predictors are fully standardized, we interpret our coefficient to mean that a one-standard-deviation increase in UGPA growth (approximately 0.43 grade points across the sample) is associated with a 0.25 standard deviation increase in 1L LGPA (approximately 0.13 grade points).

The magnitude of this relationship resembles that of final UGPA ($\beta = 0.25$; $p < .001$) but is somewhat weaker than that of LSAT score ($\beta = 0.39$; $p < .001$). To the extent that UGPA growth contributes explanatory power when predicting 1L LGPA, the similarity of effect sizes suggests that UGPA growth may be a useful supplement to traditional preadmission factors in predicting early law school academic performance (See Figure 1a below).

These findings do not meaningfully differ when excluding students who transferred undergraduate institutions, took more than four years to complete their undergraduate studies, or both transferred and completed their studies in more than four years.

1L Non-Transfer Attrition

After considering a range of potential control variables, we select a preferred model that predicts 1L non-transfer attrition as a dependent variable. The model controls for students' first-year cumulative UGPA to account for their starting place, race, and gender. (As above, neither undergraduate transfer status nor years to complete college improved model fit.)

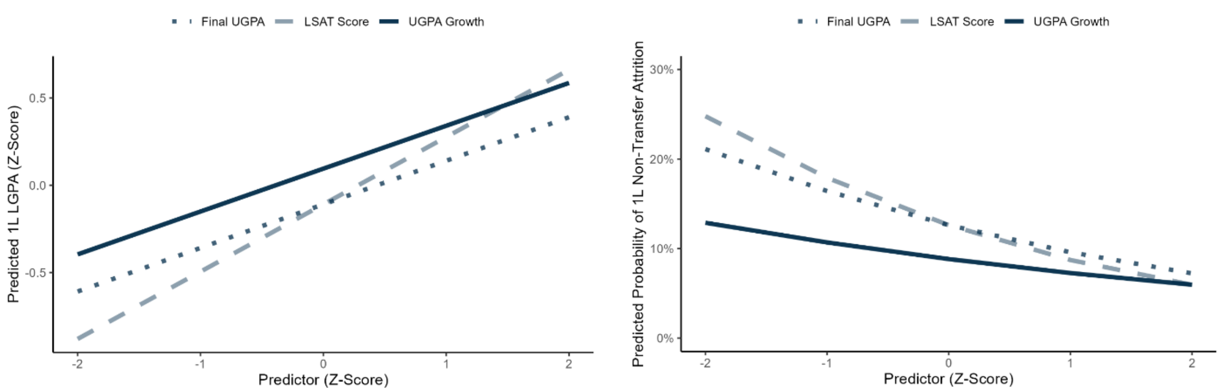
We find that UGPA growth has a negative, statistically significant relationship with the predicted probability of 1L non-transfer attrition, meaning that 1L students who matriculate with higher UGPA growth values have higher probabilities of persisting to the 2L year. ($OR = 0.81$; $p = 0.01$). A one-standard-deviation increase in UGPA growth (0.43 grade points) is associated with a two-percentage point decrease in the predicted probability of first-year attrition (from seven percent to five percent).

These effects are weaker than those of final UGPA (OR = 0.73, p = .001) and LSAT score (0.66, p = 0.001), but they are relatively comparable. This provides further support for the potential usefulness of UGPA growth as a supplementary preadmission metric, particularly to measure applicant potential for retention beyond the first year of law school (see Figure 1b below).

As with our findings related to 1L LGPA, our results here are robust to the exclusion of students who transferred undergraduate institutions, took more than four years to complete their undergraduate studies, or both transferred and completed their undergraduate studies in more than four years.

FIGURE 1
UGPA Growth Predicts Early Law School Outcomes Comparably to Final UGPA

a. **b.**



Variation by Race and Ethnicity

The similar predictive value of UGPA growth to traditional preadmission metrics is especially relevant given our descriptive finding that UGPA growth does not vary across racial and ethnic groups to the same degree as final UGPA and highest LSAT score.

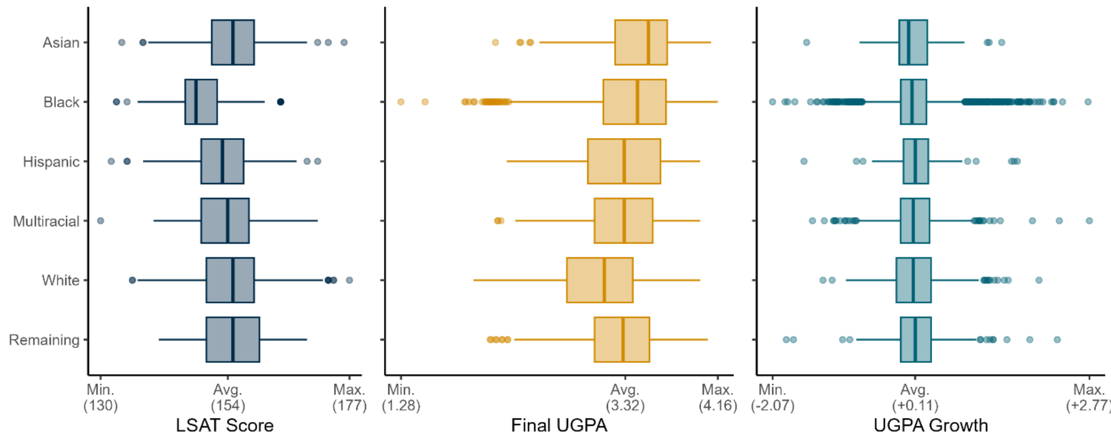
To contextualize these differences on a unified scale, we z-standardize UGPA growth, LSAT score, and final UGPA across the sample, yielding three sets of z-scores. Then we compute the mean z-score along each variable, grouped by race and ethnicity. This allows us to identify which variable — UGPA growth, LSAT score, or final UGPA — introduces the most variation by race and ethnicity on a scale of standard deviations.

From the lowest-scoring to highest-scoring racial/ethnic group, UGPA growth's average-z-score ranges from approximately $z = -0.05$ to $z = 0.07$ ($\Delta = 0.12$). Meanwhile, LSAT score ranges from $z = -0.82$ to $z = 0.16$ ($\Delta = 0.98$), and final UGPA ranges from $z = -0.59$ to $z = 0.20$ ($\Delta = 0.79$). UGPA growth therefore introduces six to eight times less variation by race and ethnicity than its traditional preadmission counterparts in our sample.

See Figure 3 for a boxplot of the differences in highest LSAT score, final UGPA, and UGPA growth by students' reported race.

FIGURE 2

Variation in LSAT Score, Final UGPA, and UGPA Growth by Race/Ethnicity



Operationalizing UGPA Growth

As we discuss above, we explore one possible vehicle by which law schools might operationalize UGPA growth via an Academic Potential Index (API). We test several iterations of the API, varying both the mathematical function used to combine each student's standardized LSAT score, final UGPA, and UGPA growth and the weights applied to each. Ultimately, we settle on a weighted sum construction of 60% LSAT score and 20% each for final UGPA and UGPA growth. This approach accounts for the most variance in 1L LGPA (i.e., yielded the highest R^2 contributions) while balancing racial equity in the index scores.

For comparison, we construct what we presume to be a reasonable approximation of a typical LSAT-UGPA index (LUI), which we calculate as the sum of a student's LSAT score and final UGPA, weighting LSAT score 60% and final UGPA 40%. Each index was converted to its z-scores for analysis.

When modeling 1L LGPA, the API yields comparable but slightly weaker predictive power than that achieved using the LUI (see Table A.4). The API and LUI predictors have betas of 0.45 and 0.53, respectively, meaning that a one-standard-deviation improvement in either index results in about a half-standard-deviation improvement in 1L LGPA. Furthermore, the API and LUI models have R^2 values of 33 and 36 percent, respectively, suggesting that each explains roughly a third of the variation in 1L LGPA. But, overall, both indices are similarly capable of predicting 1L LGPA and have strong and statistically significant effects on 1L LGPA ($p < 0.001$ in both models).

Moreover, the API yields fewer racial disparities than the LUI. The average z-score, or distance from the mean in terms of standard deviations, is lower for most racial groups along the API than the LUI. This smoothing is the direct result of including UGPA growth's influence in the index. Our testing reveals that racial differences can be further reduced by increasing the weight on UGPA growth; however, doing so reduces the explanatory power of the API.

To further probe how the use of the API might influence the racial diversity of a law school's class, we simulate how an admissions office might use the API, drawing a random sub-sample of 1,000 observations from our sample to represent a hypothetical school's applicant pool from which to admit 125 students. We make a few assumptions regarding general admissions practices, namely that schools pre-screen applicants with the highest and lowest LSAT scores and final UGPAs in order to make necessary strategic decisions regarding which applications require more care and discussion than others. We simulate this by assuming that students in our randomly-drawn sub-sample with LSAT scores and final UGPAs greater than one standard deviation above the mean are offered admission and those with one standard deviation below the mean are not offered admission. From our pool of 1,000 applications, this results in 62 initial offers of admission, leaving 63 remaining open seats and 366 applicants in the pool.

We then use the API and LUI to predict each applicant's 1L LGPA, applying school and time fixed effects as we do with our earlier analyses. We rank-order our remaining 366 applicants by their fitted values of 1L LGPA as predicted by each admission index, treating the top 63 performers by each metric as our remaining hypothetical entering class.

We find that the 63 applicants who would be admitted using the API would be more racially diverse than the 63 admitted using the LUI as the deciding factor. Using the API instead of the LUI increases the proportion of admitted applicants of color among the 63 applicants by seven percentage points (five students). The proportion of Black admittees increases by about two percentage points (one student), Hispanic admittees by three percentage points (two students), and multiracial admittees by two percentage points (one student). Although these counts may seem small, these modest improvements over time could meaningfully improve the overall racial diversity of a law school across entering classes — and meaningfully improve the experiences of underrepresented students of color on campus and in the classroom (Scott et al., 2023b). This is especially true at larger institutions, where seemingly modest percentages correspond to larger numbers of real students.

Table 2 compares the entering class profile for both overall entering classes. 62 students from each class are the same, representing applicants with both an LSAT score and final UGPA greater than one standard deviation above the mean. The remaining 63 students in each class are admitted using either the API or LUI.

TABLE 2
Comparison of Entering Classes Admitted With LUI and API

LUI	Variable	API
156.0	Median LSAT Score	157.0
3.73	Median Final UGPA	3.73
	Race (%)	
2.4	Asian	2.4
4.0	Black	4.8
5.6	Hispanic	7.2
2.4	Multiracial	3.2
82.4	White	79.2
3.2	Remaining	3.2
	Gender (%)	
48.8	Female	46.4
51.2	Male	53.6

Our simulation suggests that the integration of UGPA growth in admissions would not necessarily imply a trade-off between median LSAT and final UGPA, which bear considerable weight in law schools' admissions decisions and rankings. However, the differing class compositions represented in Table 3 suggest that UGPA growth may increase the number of admitted male students. This is a finding deserving of further study and careful consideration from admissions offices.

DISCUSSION

As outlined above, our results indicate that, in our sample, UGPA growth predicts crucial early law school outcomes similarly to LSAT score and UGPA while introducing fewer racial and ethnic gaps. The findings contribute to a body of research (1) investigating the predictive validity and potential biases of traditional law school preadmission factors and (2) exploring alternative measures to increase equity (e.g., Cunningham-Williams et al., 2018; Curcio et al., 2019; Engberg & Wolniak, 2010; Taylor et al., 2021; Taylor, 2018).

Despite the predictive power of LSAT score and final UGPA, the racial/ethnic gaps in both metrics mean their overemphasis may lead to the disproportionate exclusion of underrepresented people of color — many of whom very well might succeed if given the chance. Addressing these inequities may be difficult or impossible with traditional admission approaches — especially now that law schools can no longer consider race as part of their holistic application review processes. Meanwhile, unlike static measures of UGPA, such as final UGPA, UGPA growth better lends itself to capturing the achievements of students with delayed academic momentum — students who are more likely to come from underrepresented and low-socioeconomic-status backgrounds (Chan & Wang, 2018; Engberg & Wolniak, 2010).

Therefore, acknowledging students who overcame academic hardship in their undergraduate studies may improve racial and ethnic diversity. Consistent with this theory, in our sample, we find that UGPA growth introduces six to eight times less variation by race and ethnicity than final UGPA and LSAT score, respectively. Notably, UGPA growth achieves this relative racial equity without any direct consideration of race, deeming it permissible for use in the admission review process. Moreover, it is also easily calculable using the information conveyed to law schools as part of the standard application process.

Thus, our results provide early evidence that UGPA growth might be a helpful contributor to an emerging list of race-neutral admission tools law schools can consider in their ongoing efforts to admit racially and ethnically diverse entering classes. For example, JD-Next may hold promise as a more racially equitable admission exam capable of predicting first-semester law school GPA. Its theoretical approach broadly resembles our own; by measuring student potential for learning and growth, it prioritizes students' non-cognitive aptitudes and personality traits (Findley et al., 2023).

Alternatively, schools could use our proposed API to inform their admissions decisions. Although it may appear complex, the calculation of the index itself is relatively straightforward using the weights we suggest. But these weights are not dictated. Depending upon a school's priorities, it could adjust the weights to weaken — or strengthen — the influence of LSAT score, final UGPA, and/or UPGA growth on a case-by-case basis. In our testing, we discovered that the more weight afforded to UGPA growth, the smaller the differences between racial and ethnic groups — but this comes at the expense of explanatory power. Schools might also restrict or broaden the proportion of their applicant pool to which they apply the index, whereas we limited its application to those within one standard deviation of the mean for LSAT score and final UGPA.

As we use it, the API appears to predict 1L LGPA similarly to an index comprising only LSAT score and final UGPA. Therefore, its use should not jeopardize ABA accreditation under Standard 501. And since the API comprises LSAT score, its use would be compliant with Standard 503, which does not prescribe how "valid and reliable tests" be used in admissions decisions. Moreover, the inclusion of UGPA growth in the calculation of the API reduces the racial disparities related to LSAT scores and final UGPA. As graduate and professional programs across disciplines increasingly turn toward holistic review — and as institutions of higher education across the nation seek new ways to foster diverse learning environments post-*Students for Fair Admissions v. Harvard* — we hope these findings will help catalyze continued innovations in admissions.

Limitations

Several limitations in our study deserve mention. First, our sample only includes students admitted to law school, which limits the range of admission metrics we can observe. Future studies could pursue a broader data collection of law school applicants, rather than matriculants alone, to determine how well UGPA growth or the API index predict who is admitted to law school. In addition, this would allow researchers to compare the racial proportions of admitted and enrolled law students under a traditional index comprising LSAT score and final UGPA to those using the API. Future studies could also improve sample representation to better reflect Black, Hispanic, White, and remaining groups in closer proportions to the population and explore the possibility of examining applicants' lowest LSAT score (where available), rather than highest, to expand the range of observed test scores.

Second, our study operates under the assumption that cognitive and non-cognitive skills contribute to positive UGPA growth. Future work could collect and analyze data on undergraduate student behaviors to validate the assumption that students who achieve UGPA growth do so by improving metacognitive and non-cognitive skills, such as a growth mindset. However, regardless of the process through which students achieve UGPA growth, it is still a predictive and therefore likely useful tool in admissions.

Future studies of UGPA growth may also attempt to account for potential measurement bias associated with undergraduate GPA. For example, researchers may experiment with corrections for possible grade inflation or differences among undergraduate majors and professors. Course selection and instructor grading policies after the first year of undergraduate study may influence UGPA growth. Although we lack the data to test this in the current study, future work might investigate the courses through which students improve their UGPAs over time, contributing to our understanding of whether UGPA growth may interact with course rigor. For example, it would be worthwhile to examine whether students who improve their UGPAs do so by self-selecting into more leniently graded courses. Nevertheless, our results suggest that UGPA growth predicts first-year LGPA similarly to LSAT score and final UGPA.

Finally, we offer a limited overview of ways to operationalize and consider UGPA growth in a law school admissions context. Our API was not the primary focus of this research; rather, it was conceived in response to our findings related to UGPA growth. A full simulation study might yield a more robust index. Furthermore, our simple simulation of its use does not account for additional application materials that law schools routinely consider when making admission decisions.

Future researchers may take myriad approaches to constructing the index, both in the mathematical function and weighting used to combine the variables. Furthermore, we focused on constructing an index that was simple and easily calculable using data that is readily available to law schools. Future generations of the API might include additional criteria beyond LSAT score, final UGPA, and UGPA growth. These iterations should aim to balance the relative availability of the data upon which the index relies and the practicability of the index with greater explanatory power and equity in the admission outcomes. Further study could explore the generalizability of these findings to higher education more broadly.

CONCLUSION

Our findings suggest that UGPA growth could play an important role in the future of law school admissions. We find that UGPA growth, among our sample, successfully predicts 1L LGPA and 1L non-transfer attrition comparably to LSAT score and final UGPA. In the face of a changing admissions landscape and the push for more holistic application review, UGPA growth — either alone or as part of an index — might hold promise as a tool for continued development and consideration. Furthermore, we find that UGPA growth may result in fewer racial disparities in admissions, while remaining race-neutral and legally permissible. As graduate and professional programs and institutions of higher learning seek new ways to foster diverse learning environments following the *Students for Fair Admissions v. Harvard* decision, we hope these findings will help encourage persistent and innovative efforts to make law school admissions more equitable.

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APPENDIX

TABLE A.1

Summary Statistics

Variables	N	%	Min	Q1	Med	Mean	Q3	Max	SD	IQR
Law School										
Age at Matriculation	5139		17	23	24	25.9	27	75	5.28	4
1L LGPA	5363		0.33	2.66	3.04	3.00	3.37	4.30	0.50	0.71
1L Non-Transfer Attrition: Yes	268	7.29								
Final LGPA	4079		1.71	2.84	3.14	3.12	3.41	4.25	0.40	0.57
Preadmission										
Undergraduate Institution Admit Rate	4711		0.05	0.52	0.65	0.62	0.75	1.00	0.19	0.23
First Year Undergraduate GPA	5599		1	2.88	3.3	3.21	3.67	4.33	0.59	0.79
Final Undergraduate GPA	5599		1.28	3.06	3.37	3.32	3.64	4.17	0.42	0.58
Undergraduate GPA Growth	5599		-2.07	-0.11	0.07	0.11	0.30	2.77	0.43	0.41
Highest LSAT Score	5560		130	150	154	154.0	158	177	6.16	8
Undergraduate Transfer: Yes	2776	57.49								
Years to Complete Undergraduate	4522									
Four or fewer	2448	54.14								

TABLE A.2
UGPA Growth's Effect on 1L LGPA and Attrition

	LGPA: Null Model	LGPA: Maximal Model	LGPA: Preferred Model	Attrition: Null Model	Attrition: Maximal Model	Attrition: Preferred Model
UGPA Growth	0.26 *	0.26 *	0.25 *	-0.20 *	-0.22 *	-0.21 *
	[0.22; 0.31]	[0.20; 0.31]	[0.20; 0.29]	[-0.34; -0.06]	[-0.38; -0.06]	[-0.32; -0.10]
First Year UGPA	0.38 *	0.38 *	0.35 *	-0.46 *	-0.42 *	-0.39 *
	[0.31; 0.44]	[0.30; 0.46]	[0.29; 0.42]	[-0.64; -0.28]	[-0.59; -0.24]	[-0.56; -0.22]
UGPA Growth and First Year UGPA (Interaction)					-0.07 *	-0.06 *
					[-0.12; -0.02]	[-0.10; -0.01]
Undergraduate Admit Rate		-0.09 *	-0.10 *			
		[-0.13; -0.05]	[-0.14; -0.06]			
Gender: Male		0.07 *	0.07 *			
		[0.02; 0.12]	[0.03; 0.11]			
Race: Black		-0.14	-0.12		0.05	-0.17
		[-0.40; 0.12]	[-0.33; 0.09]		[-0.50; 0.60]	[-0.61; 0.28]
Race: Hispanic		-0.13	-0.08		-0.86 *	-0.51
		[-0.38; 0.12]	[-0.29; 0.13]		[-1.53; -0.18]	[-1.02; 0.01]
Race: Two or More Races		0.05	0.11		-0.27	-0.29
		[-0.18; 0.27]	[-0.09; 0.31]		[-1.56; 1.02]	[-1.51; 0.93]
Race: Remaining		0.32 *	0.35 *		-0.78	-0.74
		[0.12; 0.52]	[0.17; 0.52]		[-3.33; 1.76]	[-2.49; 1.02]
Race: Unknown		0.25 *	0.38 *		-0.30	-0.34 *
		[0.14; 0.36]	[0.14; 0.62]		[-0.75; 0.14]	[-0.62; -0.06]
Race: White		0.25 *	0.30 *		-0.61 *	-0.61 *
		[0.07; 0.44]	[0.14; 0.46]		[-1.08; -0.13]	[-0.93; -0.30]
Age at Matriculation		0.04			0.02	
		[-0.00; 0.07]			[-0.12; 0.16]	
Years to Graduate, College: > 4		0.03			0.15	
		[-0.05; 0.12]			[-0.29; 0.59]	
Undergraduate Transfer		-0.08 *			-0.11	
		[-0.15; -0.01]			[-0.47; 0.24]	
Num. obs.	4055	3500	4055	3671	3064	3671
Num. groups: schools	9	8	9	7	6	7
Num. groups: years	9	9	9	9	9	9
R^2	0.30	0.35	0.33			
Deviance				1752.40	1321.71	1741.13
Log Likelihood				-876.20	-660.86	-870.56
Tjur's R^2				0.07	0.09	0.07

Note: CI refers to the 95 percent confidence intervals for the estimate. The reference group for student race is Asian or Pacific Islander.

TABLE A.3
Effect of LSAT/UGPA on 1L LGPA and Attrition

	LGPA: Null Model	LGPA: Maximal Model	LGPA: Preferred Model	Attrition: Null Model	Attrition: Maximal Model	Attrition: Preferred Model
Top LSAT Score	0.41 *	0.39 *	0.39 *	-0.40 *	-0.35 *	-0.41 *
	[0.31; 0.51]	[0.28; 0.50]	[0.28; 0.49]	[-0.57; -0.23]	[-0.60; -0.10]	[-0.63; -0.19]
Final UGPA	0.26 *	0.26 *	0.25 *	-0.32 *	-0.32 *	-0.31 *
	[0.22; 0.29]	[0.22; 0.30]	[0.21; 0.29]	[-0.44; -0.21]	[-0.48; -0.16]	[-0.41; -0.20]
Undergraduate Admit Rate		-0.06 *	-0.07 *		-0.04	
		[-0.10; -0.02]	[-0.11; -0.03]		[-0.20; 0.11]	
Race: Black		0.01	0.04		-0.24	-0.47
		[-0.24; 0.25]	[-0.16; 0.24]		[-0.77; 0.28]	[-0.94; 0.01]
Race: Hispanic		-0.07	-0.03		-0.91 *	-0.68 *
		[-0.29; 0.16]	[-0.21; 0.16]		[-1.65; -0.17]	[-1.27; -0.10]
Race: Two or More Races		0.05	0.11		-0.26	-0.28
		[-0.23; 0.32]	[-0.14; 0.35]		[-1.63; 1.10]	[-1.57; 1.00]
Race: Remaining		0.30 *	0.33 *		-0.73	-0.65
		[0.16; 0.45]	[0.20; 0.46]		[-3.27; 1.81]	[-2.41; 1.11]
Race: Unknown		0.07	0.19		-0.13	-0.09
		[-0.09; 0.23]	[-0.05; 0.43]		[-0.56; 0.31]	[-0.36; 0.18]
Race: White		0.15	0.20 *		-0.56 *	-0.56 *
		[-0.07; 0.37]	[0.01; 0.38]		[-1.02; -0.11]	[-0.87; -0.25]
Age at Matriculation		0.03				
		[-0.00; 0.06]				
Years to Graduate, College: > 4		0.04			0.15	
		[-0.04; 0.12]			[-0.30; 0.59]	
Undergraduate Transfer		-0.06			-0.11	
		[-0.12; 0.00]			[-0.41; 0.19]	
Num. obs.	4037	3482	4037	3436	2849	3436
Num. groups: sch.id	9	8	9	7	6	7
Num. groups: matric.yr	9	9	9	9	9	9
R^2	0.40	0.43	0.41			
Deviance				1647.62	1251.35	1639.56
Log Likelihood				-823.81	-625.68	-819.78
Tjur's R^2				0.08	0.08	0.07

Note: CI refers to the 95 percent confidence intervals for the beta coefficient or odds ratio. The reference group for student race is Asian or Pacific Islander.

TABLE A.4

Comparison of API and LUI

	Effect on 1L LGPA	
Academic Potential Index	0.45 ***	
	(0.04)	
LSAT/UGPA Index		0.53 ***
		(0.04)
Observations	5,323	5,323
Groups: Schools	14	14
Groups: Years	10	10
R^2 (full model)	0.33	0.36