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What Predicts Law Student Success? A Longitudinal Study Correlating Law Student Applicant Data and Law School Outcomes

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What Makes a Law Student Succeed or Fail? A Longitudinal Study Correlating Law Student Applicant Data and Law School Outcomes

Alexia Brunet Marks and Scott A. Moss[*]

Despite the rise of "big data" empiricism, law school admission remains heavily impressionistic; admission decisions based on anecdotes about recent students, idiosyncratic preferences for certain majors or jobs, or mainly the Law School Admission Test (LSAT). Yet no predictors are well-validated; studies of the LSAT or other factors fail to control for college quality, major, work experience, etc. The lack of evidence of what actually predicts law school success is especially surprising after the 2010s downturn left schools competing for fewer applicants and left potential students less sure of law school as a path to future success. We aim to fill this gap with a two-school, 1400-student, 2005-2012 longitudinal study. After coding non-digitized applicant data, we used multivariate regression analysis to predict law school grades ("LGPA") from many variables: LSAT; college grades ("UGPA"), quality, and major; UGPA trajectory; employment duration and type (legal, scientific, military, teaching, etc.); college leadership; prior graduate degree; criminal or discipline record; and variable interactions (*e.g.*, high-LSAT/low-UGPA or vice-versa).

Our results include not only new findings about how to balance LSAT and UGPA, but the first findings that college quality, major, work experience, and other traits are significant predictors: (1) controlling for other variables, LSAT predicts more weakly, and UGPA more powerfully, than commonly assumed – and a high-LSAT/low-UGPA profile may predict worse than the opposite; (2) a STEM (science, technology, engineering, math) or EAF (economics, accounting, finance) major is a significant plus, akin to 3½-4 extra LSAT points; (3) several years' work experience is a significant plus, with teaching especially positive and military the weakest; (4) a criminal or disciplinary record is a significant minus, akin to 7½ fewer LSAT points; and (5) long-noted gender disparities seem to have abated, but racial disparities persist. Some predictors were interestingly nonlinear: college quality has *decreasing* returns; UGPA has *increasing* returns; a *rising* UGPA is a plus only for law students right out of college; and 4-9 years of work is a "sweet spot," with neither 1-3 or 10+ years' work experience significant. Some, such as those with military or science work, have *high LGPA variance*, indicating a mix of high and low performers requiring close scrutiny. Many traditionally valued traits had no predictive value: typical pre-law majors (political science, history, etc.); legal or public sector work; or college leadership.

These findings can help identify who can outperform overvalued predictors like the LSAT. A key caveat is that statistical models cannot capture certain difficult-to-code key traits: some who project to have weak grades retain appealing lawyering or leadership

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potential; and many will over- or under-perform any projection. Thus, admissions will always be both art and science – but perhaps with a bit more science.

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The modern legal education crisis – years of rising tuition and legal sector retrenchment[1] yielding declining law school applications[2] – put a premium on a question that always should have mattered to law schools and their students: What qualities predict law student success? This concern has grown as the downturn has left schools competing for far fewer applicants: applications are at a 30-year low,[3] down 38% over two years alone,[4] forcing schools to shrink, decrease selectivity, or both.[5] Part of the decline may be cyclical, but there also are core long-term, structural causes: the obsolescence of the large-firm model, especially as clients

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[1] National Association for Law Placement (hereinafter "NALP") statistics show that only 86% of 2011 graduates obtained paying jobs, with less than 66% of those requiring a law license. Joe Palazzolo & Chelsea Phipps, *With Profession Under Stress, Law Schools Cut Admissions*, WALL ST. J., June 11, 2012, http://online.wsj.com/article/SB10001424052702303444204577458411514818378.html. Many of the latter job category, moreover, were mere contract work, which is by definition non-permanent and only pays around $25/hour. Jordan Weissmann, *Law School Applications Are Collapsing (as They Should Be)*, THE ATLANTIC (Jan. 2013), http://www.theatlantic.com/business/archive/2013/01/law-school-applications-are-collapsing-as-they-should-be/272729/.

[2] *See* Richard Susskind, *Tomorrow's Lawyers, Vol. 39 No. 4*. A.B.A. L. PRAC. MAG., July/Aug. 2013, available at http://www.americanbar.org/publications/law_practice_magazine/2013/july-august/tomorrows-lawyers.html (noting that law schools are "under fire" for admitting more students than the likely number of law jobs); BRIAN Z. TAMANAHA, FAILING LAW SCHOOLS (2012) (arguing that modern law schools lack sustainable business models due to increased tuition and decreased employment rates); STEPHEN HARPER, THE LAWYER BUBBLE: A PROFESSION IN CRISIS 124 (2013) (detailing layoffs and closures at previously large, successful law firms).

[3] Ethan Bronner, *Law Schools' Applications Fall as Costs Rise and Jobs Are Cut*, N.Y. TIMES (Jan. 30, 2013), http://www.nytimes.com/2013/01/31/education/law-schools-applications-fall-as-costs-rise-and-jobs-are-cut.html.

[4] Paul Lippe, *D-Day for Law School Deans*, A.B.A. J. (May 1, 2013), http://www.abajournal.com/legalrebels/article/d-day_for_law_school_deans (noting clients' new unwillingness to subsidize associate training by paying hourly rates for inexperienced lawyers).

[5] Palazzolo & Phipps, *supra* note 1.

began demanding experienced lawyers, not higher-profit-margin junior lawyers;[6] the rise of a legal process outsourcing industry as digitization allows offsite work;[7] and cheaper competition, as technology streamlines high-markup labor-intensive tasks, from simple software for creating simple documents[8] to replacing multi-lawyer document review with "predictive coding" in which "machine algorithms partially replac[e] humans altogether in the search for relevant information."[9]

With schools seeing fewer applicants, all schools have been forced to admit students with lower numerical predictors. Especially in a diminished pool, discerning who likely can outperform their numbers is an imperative. Elite schools want to keep admitting those who pass bar exams at high rates and display the talent to land elite jobs; non-elite schools want those who, despite low grades or LSAT scores, still can perform competent legal work and pass a bar exam. The interests are similar from applicants' perspective. Those with strong LSAT/grade profiles do not always win admission to top schools, and ideally those who are truly stronger should win those coveted seats; those with weak LSAT/grade profiles may not win admission to a reputable (or any) school, yet it is a loss for society and the profession if the stronger low-numbers candidates lack good (or any) admission offers. More broadly, the value of students getting admission offers they deserve goes beyond this era of fewer in law applications. Even if applications rise, schools and students still should want to know who projects to succeed or fail based on factors other than the obvious, such as LSAT, and factors of unclear import, such as college major. Even if the tide rises or some schools can stand pat, the innovative gain advantage from better projecting which prospects are more (or less) promising than they first appear.

Yet law school admission decisions are less data-driven than impressionistic, often basing on anecdotes (*e.g.*, admitting those resembling recent stars, not those like recent underachievers), on idiosyncratic preferences (*e.g.*, for certain majors or jobs), or heavily numerical criteria (*e.g.*, a high LSAT nearly guaranteeing admission).[10] The studies on law school success control for few or no other

[6] Marc Galanter & William Henderson, *The Elastic Tournament: A Second Transformation of the Big Law Firm*, 60 STAN. L. REV. 1867 (detailing evolution of associate-heavy large firms from a classic (inverted funnel) pyramid with a standard tournament model to "core and mantle" pyramids with "elastic" tournaments); Lippe, *supra* note 4.

[7] *See* SUSSKIND, THE END OF LAWYERS? 27-57; *Law Firms Are Losing Work to LPO Providers*, MANAGING PARTNER (Sept. 3, 2012), http://www.managingpartner.com/news/business-strategy/law-firms-are-losing-work-lpo-providers [hereinafter *Law Firms Losing Work*] (noting overseas LPO alone now exceeds $1 billion).

[8] Deborah L. Jacobs, *The Case Against Law School*, FORBES (Jan. 31, 2013), http://www.forbes.com/sites/deborahljacobs/2011/10/11/the-case-against-law-school (recounting how a group of venture capitalists, including Google, invested $18.5 million in Rocket Lawyer, while LegalZoom raised $66 million in venture capital the month before).

[9] William D. Henderson, *A Blueprint for Change*, 40 PEPP. L. REV. 461, 487 (2013).

[10] The authors have served for years as Chair (Moss) and Vice-Chair (Marks) of the University of Colorado Law School Faculty Admissions Committee, casting votes on thousands of applicants. So their critique of law school admissions is not a criticism of others; it is an effort

variables in finding that LSAT correlates with first-year law grades, or that a certain interpersonal quality is a plus. Studies with one or only a few variables leave unclear whether a seemingly significant variable is a true predictor, or is simply correlated with another predictor, or is a weaker predictor when other variables are evaluated simultaneously. For example, do high-LSAT students really do better, or does a high LSAT just correlate with other predictors, such as attending a strong college? Do any majors, like traditional pre-law majors such as political science or history, predict success or failure, or is there no difference among majors? And what of key interactive mixes of variables – for example, which kind of "splitter" does better, the high-LSAT/low-UGPA college student or the reverse? No prior study has examined who succeeds with a broad range of actual data allowing testing of the individual impact of as many measurable metrics as possible – a gap this Article aims to fill.

This Article details the methodology and findings of a longitudinal study based on data spanning 2005 to 2012, from over 1400 students, at two law schools, Case Western Reserve University and the University of Colorado Law Schools. The study examines how data in the students' 2005-2008 law school applications correlate with their 2006-2011 grades - an effort requiring a substantial undertaking to code data from paper files and to merge separate admissions and registrar databases. The study attempts to predict law school grade-point average ("LGPA") as a function of numerous independent variables: LSAT score; undergraduate grade-point average ("UGPA"); college quality, as measured by a metric available for virtually all colleges, the mean LSAT of students at the college ("LCM"); college major; years, and type, of full-time work; significant extracurricular leadership; having another graduate degree; having a substantially rising UGPA; negative criminal or academic misconduct records; and various interactions of these variables (*e.g.*, having a high LSAT but low UGPA, or vice-versa; or only those who just graduated college having a rising UGPA, on the theory that UGPA trajectory matters more for those right out of college). Most of this data did not exist in digital form and therefore had to be manually entered; for example, college majors are listed on transcripts, years and type of work experience are listed on applicants' résumés, and criminal/disciplinary records are submitted with law applications. Other data were digitized but required manual review to enter the relevant variables; for example, UGPAs are digitized, but not whether UGPAs rose during college, requiring review of year-to-year grades.

Our results include not only new findings about how to balance LSAT and UGPA, but also the first statistical findings that college quality, major, work experience, and other variables are significant predictors: (1) controlling for other variables, LSAT predicts more weakly, and UGPA more powerfully, than commonly assumed – and a high-LSAT/low-UGPA profile predicts worse than a high-UGPA/low-LSAT profile; (2) a STEM (science, technology, engineering,

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to improve their own and others' admissions work alike.

math) or EAF (economics, accounting, finance) major is a significant plus, akin to having 3½-4 extra LSAT points; (3) several years' work experience is a significant plus, with teaching especially positive, and military the weakest; (4) a criminal or disciplinary record is a significant minus, akin to 7½ fewer LSAT points; and (5) long-noted gender disparities appear to have abated, but racial disparities persist. Some predictors were interestingly nonlinear: college quality has *decreasing* returns; UGPA has *increasing* returns; a *rising* UGPA is a plus for only those right out of college; and 4-9 years of work is the "sweet spot," with 1-3 and over 10 not significant. Some students display *high LGPA variance*, indicating a mix of high and low performers requiring close scrutiny – *e.g.*, those with military or science work. Finally, many traits traditionally seen as plusses had no predictive value: common pre-law majors like political science or history; legal or public sector work; and college leadership. Most findings proved robust across various specifications.

These findings have key caveats. First, law grades are incomplete predictors of contribution to society, career fulfillment, or even long-term job prospects, given that law grades predict lawyers' earnings for only their first several years;[11] many applicants predicted to have middling grades are appealing for reasons, such as leadership, diversity, and intangible qualities. Second, no statistical model captures all human qualities, and many traits are not readily reducible to data; many will over- or under-perform even the best predictions, so talent assessment is more art than science. Third, negative predictors are not consistent across individuals: some groups that project poorly are a heterogeneous mix that individualized scrutiny can distinguish; and certain predictors are not consistent over time, such as predictors that are negative just because some people need more time to adjust to law study.

Given the above three caveats, we in no way suggest that simply including enough variables makes admissions reducible to a formula. Even with these caveats, law grades are useful as predictors – of the bar passage that is necessary to most lawyer jobs, of gaining employment in the first several years after law school, and of at least some aspects of legal acumen. Our findings thus should inform law schools tasked with difficult decisions: who among numerically similar applicants is most promising; who can outperform their LSAT and UGPA enough to warrant admission or scholarship offers; and which traditionally valued or under-valued qualities truly are, or are not, provable predictors of success. And later work on the same data set will explore further the extent to which the law school applicant qualities predict post-law school bar passage and employment, not just law grades.

This Article proceeds as follows. Part II analyzes the literature on what qualities affect student success and on the limited, mainly univariate, empirical

[11] Jeffrey E. Stake et al., *Income and Career Satisfaction in the Legal Profession: Survey Data from Indiana Law Graduates*, 4 J. EMPIRICAL LEG. STUD. 939, 970, 973 (2007) (finding that five years after law school, "each additional 0.1 on the graduate's [L]GPA yields $3,449 in additional annual income," but by fifteen years after law school, LGPA has no effect on income).

analyses of student traits. Part III details our methodology – how and what data was procured, and our statistical models. Part IV, the core of the Article, details our findings: which variables proved significant positive or negative LGPA predictors; the relative magnitudes of the variables' effects, *e.g.*, how much in UGPA, college quality, or work experience is akin to an extra LSAT point; and our interpretations of what these findings show about various students' law school prospects. Part IV notes that while the vast literature on law school reform is beyond this Article's scope, our findings do provide new evidence supporting some reforms and undercutting others. A brief Conclusion previews future work predicting employment and bar exam outcomes based on this Article's data set, and other similarly obtainable data, if law schools devote resources to similar analytics in the future – as we hope they do.

II. BACKGROUND: PRIOR STUDY OF DESIRABLE STUDENT TRAITS AND SUCCESS PREDICTORS

This Part divides the literature on factors predicting success into three categories: (A) the impact of *academic factors*, including LSAT, UGPA, and other college record information; (B) the impact of varied *learning strategies*, from reading styles to professional orientation; and (C) the impact of *personal qualities*, such as emotional intelligence, resilience, and maturity. We discuss three ways this Article aims to fill gaps in that literature. First, various factors that may predict success or failure have drawn little or no prior analysis because they are not coded in statistics-friendly digital form – such as college major, duration and kind of work experience, and criminal record. Second, where no clear data exist on a potentially important quality, such as interpersonal skills, resilience, or maturity, we propose certain variables as proxies – for example, leadership role as a proxy for interpersonal skill, rising UGPA after a weak college start as a proxy for resilience, or disciplinary or criminal record as a proxy for lack of maturity. Third, most studies are univariate, simply finding correlations between success and one factor without controlling for, or examining interactions with, other factors.

A. The Value of Academic and Numerical Qualities: LSAT, UGPA, and Factors Moderating UGPA

Law schools strongly eye a few numerical indicators. In particular, median LSAT is a top driver of a school's reputation: among innumerable qualities students possess, LSAT alone is worth 12.5% of the *U.S. News & World Report* law school rankings.[12] But William Henderson found that this linear weight understates the impact of LSAT on school rank, in a study aiming to "identify the relative winners and losers over time in the competition for the finite number of high-LSAT students, and examine … factors that can explain the underlying pattern in the movements of LSAT scores at law schools."[13] Henderson found that

[12] William D. Henderson & Andrew P. Morriss, *Student Quality as Measured by LSAT Scores: Migration Patterns in the U.S. News Rankings Era*, 81 INDIANA L. J. 163 (2006).
[13] *Id.* at 169.

90% of differences in schools' ranks can be explained solely by median LSAT, which both varies greatly among schools and is more readily "gamed" by schools, at all rankings levels,[14] than other major rank components, such as school reputation.[15]

Partly because it drives school rank, LSAT is by far the dominant admissions factor, even compared to UGPA, the main other numerical predictor. The "Law School Probability Calculator," which estimates admission odds by LSAT and UGPA from thousands of data points,[16] shows a vast gap between the fates of the two "splitter" applicant types: high LSAT with a low UGPA; and low LSAT with a high UGPA. Illustrating schools' preference for high-LSAT over high-UGPA splitters is anecdotal evidence from two examples of mid-tier schools, Santa Clara University and St. John's University (which have very similar LSAT and UGPA medians)[17] and two highly-ranked schools, Georgetown University Law Center and University of Michigan Law School (also with very similar LSAT and UGPA medians).[18]

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[14] *Id.* at 191 (noting that statistics for transfer students and, until recently, entering part-time students were not included in rankings, so a school could raise median LSAT by shrinking the full-time program and expanding transfer and part-time admissions, and top-tier schools are better-positioned to stay selective and admit transfer students to make up for revenue losses).

[15] *Id* at 165. Henderson and Morriss specifically found as follows: (1) the legal education market is segmented into a national market, roughly the current top quarter ("Tier 1") of law schools, and a regional market encompassing the rest of the law school hierarchy; (2) within each segment, a higher initial starting position was associated with increases in median LSAT; (3) in quarter 2-4, lower-cost schools have a better yield of high-LSAT students, but in quarter 1, prestige is more important than price; (4) in quarters 2-4, law schools in major Am Law 200 markets have a significant advantage in attracting high-LSAT students; and (5) in quarters 2-4, changes in lawyer/judge and academic reputations are unrelated to changes in median LSAT whereas in quarter 1, an increase in academic reputation is associated with higher LSAT. *Id*. at 182-88 (further noting that the median LSAT of top-16 schools has increased an average of 1.69 points, while schools that began in quarter 2 had a 0.45 increase in their median LSAT scores, and schools in quartiers 3 and 4 experienced declines of -1.56 and -1.34, *id*. at 186).

[16] *Law School Probability Calculator*, http://www.hourumd.com (last visited Feb. 26, 2015) (explaining that it "uses data gathered from Law School Numbers to calculate probability of admission at various law schools. All data is self-reported, but with over 143,000 data points, it should be somewhat accurate").

[17] These schools were chosen simply because they are law schools on opposite coasts but close to the middle of the rankings, with similar median LSAT and UGPA statistics: 3.21/157 for Santa Clara, *2013 Class Profile*, SANTA CLARA L., http://law.scu.edu/admissions/2013-class-profile (last visited Feb. 26, 2015); 3.39/156 for St. John's, *FAQs*, ST. JOHN'S UNIV. SCH. OF L. http://www.stjohns.edu/law/admissions/faqs (last visited Feb. 26, 2015).

[18] Georgetown's medians are a 3.75 GPA and 168 LSAT. *Stats, Facts & More*, GEO. UNIV. L. CTR., http://www.law.georgetown.edu/admissions-financial-aid/jd-admissions/full-time-part-time-program/faqs/General.cfm (last visited Feb. 26, 2015). Michigan's are a 3.71 GPA and 168 LSAT. *Class Statistics*, UNIV. MICH. L. SCH., http://www.law.umich.edu/prospectivestudents/pages/classstatistics.aspx (last visited Feb. 26, 2015).

- ***Santa Clara University Law School*** admitted 94% of those with an above-median 158-160 LSAT and a below-median 3.0-3.2 UGPA,[19] but only 40% of those with a reverse LSAT/UGPA profile that is roughly equivalent in distance from the school's medians[20] – an above-median 3.7-3.9 UGPA, and a below-median 151-153 LSAT.[21]

- ***St. John's University Law*** **School** was almost exactly the same as Santa Clara, admitting 100% with the same above-median LSAT and below-median UGPA (158-160/3.0-3.2),[22] but 37.5% with the same above-median UGPA and below-median LSAT (3.7-3.9/151-153). [23]

- ***Georgetown University Law Center*** admitted 83.02% with an above-median LSAT and below-median UGPA (170-172/3.2-3.4),[24] but 38.3% of those with a reverse LSAT/UGPA profile that is roughly equivalent in distance from the school's medians – an above-median 3.8-4.0 UGPA, and a below-median 164-166 LSAT. [25]

- ***University of Michigan Law School*** was almost exactly the same as Georgetown, admitting 75.51% with the same above-median LSAT and below-median UGPA (170-172/3.2-3.4),[26] but 34.45% with the same above-median UGPA and below-median LSAT (3.8-4.0/164-166).[27]

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[19] *Law School Probability Calculator*, query: http://www.hourumd.com/?lsat=160-162&gpa=3.0-3.2&money=no&urm=yes&waitlist=yes&range=no (last visited Feb. 26, 2015).

[20] As detailed below, one LSAT point is, roughly, equivalent to 0.03-0.06 in UGPA, a shorthand useful for comparing high-UGPA/low-LSAT "splitters" to the reverse splitter type. We cannot know whether each of these four schools (St. John's, Santa Clara, Georgetown, and Michigan) would agree that these opposite profiles are equivalent in distance from their medians, so possibly they believed the low-UGPA/high-LSAT group to be weaker than the opposite high-UGPA/low-LSAT group. Still, our findings indicate that these opposite-profile groups are roughly in par with each other, so the difference is striking, and strikingly consistent, between the fate of the high-UGPA/low-LSAT splitters (34-40% admitted at each of the four schools) and the high-LSAT/low-UGPA splitters (75-100% admitted at each of the four schools).

[21] *Law School Probability Calculator*, query: http://www.hourumd.com/?lsat=151-153&gpa=3.7-3.9&money=no&urm=yes&waitlist=yes&range=no (last visited Feb. 26, 2015).

[22] *Law School Probability Calculator*, query: http://www.hourumd.com/?lsat=160-162&gpa=3.0-3.2&money=no&urm=yes&waitlist=yes&range=no (last visited Feb. 26, 2015).

[23] *Law School Probability Calculator*, query: http://www.hourumd.com/?lsat=151-153&gpa=3.7-3.9&money=no&urm=yes&waitlist=yes&range=no (last visited Feb. 26, 2015).

[24] *Law School Probability Calculator*, query: http://www.hourumd.com/?lsat=170-172&gpa=3.2-3.4&money=no&urm=yes&waitlist=yes&range=no (last visited Feb. 26, 2015).

[25] *Law School Probability Calculator*, query: http://www.hourumd.com/?lsat=164-166&gpa=3.8-4.0&money=no&urm=yes&waitlist=yes&range=no (last visited Feb. 26, 2015).

[26] *Law School Probability Calculator*, query: http://www.hourumd.com/?lsat=170-172&gpa=3.2-3.4&money=no&urm=yes&waitlist=yes&range=no (last visited Feb. 26, 2015).

[27] *Law School Probability Calculator*, query: http://www.hourumd.com/?lsat=164-166&gpa=3.8-4.0&money=no&urm=yes&waitlist=yes&range=no (last visited Feb. 26, 2015).

Though schools clearly weight LSAT over UGPA, evidence the LSAT truly predicts law grades is underwhelming. The few findings on LSAT predictive power are mixed and fail to control for other key variables. The most prominent studies are by LSAC, the Law School Admission Council – a hardly unbiased source, because it is the entity that is "best known for administering the … LSAT[], with about 100,000 tests administered annually," and that "publishes LSAT preparation books and law school guides, among many other services" it sells.[28] LSAC reports that "LSAT scores help to predict which students will do well in law school."[29] But it also admits that its studies show only that LSAT correlates with *first-year* grades:

> [M]ost law schools have participated in studies that have compared students' LSAT scores with their *first-year* grades. … *[T]hese studies show that LSAT scores help to predict which students will do well in law school*. … [T]he combination of … LSAT score and undergraduate grade-point average yields a better prediction … than either measure used alone. … [C]orrelations between average LSAT score and *first-year* law school grades ranged [among schools] from .16 to .54, with a median … of .36. … [C]orrelations between UGPA and first-year law school grades ranged from .09 to .45, with a median … of .28. … [C]orrelations between the combination of average LSAT score and undergraduate grades with first-year … grades ranged from .27 to .63, with a median … of .46.[30]

Similar studies found that LSAT better predicted *first-year law grades*[31], while UGPA predicted *overall grades*[32], and a combined LSAT/UGPA index was better

[28] LSAC describes itself as follows:

> LSAC[] is a nonprofit corporation … best known for … [the] LSAT …. LSAC also processes academic credentials for an average of 60,000 law school applicants annually, provides essential software and information for admission offices and applicants, conducts educational conferences … , sponsors and publishes research, funds diversity and other outreach … , and publishes LSAT preparation books and law school guides.

About LSAC, LAW SCHOOL ADMISSIONS COUNCIL, http://www.lsac.org/aboutlsac/about-lsac (last visited July 28, 2014).

[29] LAW SCHOOL ADMISSION COUNCIL, 2012–2013 LAW SCHOOL ADMISSION REFERENCE MANUAL 11 (2012).

[30] *Id*. (emphases added).

[31] Marjorie M. Shultz & Sheldon Zedeck, *Predicting Law Effectiveness: Broadening the Basis for Law School Admission Decisions*, 36 LAW & SOC. INQUIRY 620, 622 (2011).

[32] David A. Thomas, *Predicting Law School Academic Performance From LSAT Scores and Undergraduate Grade Point Averages: A Comprehensive Study*, 35 ARIZ. ST. L.J. 1007, 1021 (2003). *See also* Neal Schmitt, Jessica Keeney and Fredrick L Oswald, (2009), *Prediction of 4-year College Student Performance Using Cognitive and Noncognitive Predictors and the Impact on Demographic Status of Admitted Students,* Journal of Applied Psychology, vol. 94, no. 6, 1479-1497 (this study also uses graduation as a measure of success and shows that the most important predictor of college graduation status was high school grades).

than either alone at predicting *both* first-year and overall law school grades.[33] These studies indicate that while both LSAT and UGPA have predictive power, the LSAT perhaps should not be given disproportionate weight. These studies also raise further questions about how predictive each of LSAT and UGPA would be in a study that controls for other variables about students' personal and college backgrounds.

A study of the similar Master's in Business Administration ("MBA") admissions process, which typically bases heavily on UGPA and the LSAT-like Graduate Management Admission Test ("GMAT"), similarly found UGPA more important than the standardized test: GMAT did predict MBA grades, but to a limited degree;[34] UGPA predicted grades better than GMAT verbal and quantitative scores;[35] and a combination of all predictors (UGPA and GMAT verbal and quantitative scores) predicted better than any factor alone.[36] The study noted that schools should not rely on GMAT and UGPA to the exclusion of other factors, such as motivation and work experience, yet did not control for such difficult-to-quantify factors.[37]

Even if the LSAT helps predict LGPA, it may do so for a less substantive reason: test-taking speed helps determine performance on the LSAT and traditional in-class law exams that produce most law grades.[38] William Henderson notes that the LSAT is a stronger predictor of timed, in-class exam grades than of take-home exam or research paper grades:[39] "on take-home exams and papers, … it appears that the LSAT is actually a weaker predictor of law school performance than UGPA," which measures a composite of reasoning, writing, motivation, and persistence.[40] Thus, a school's emphasis on timed in-class exams increases the predictive power of a timed in-room exam like the LSAT. Yet test-taking speed is not a meaningful intelligence measure, Henderson notes: "[w]ithin the field of psychometrics, test-taking speed and reasoning ability are viewed as distinct, separate abilities with little or no correlation."[41] And while the old model of legal education consisted mainly of timed, in-class tests, schools have shifted to a

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[33] *Id.* at 1011 (summarizing aggregate correlation scores for students in all twenty-seven classes: LSAT and 1L rank, 0.744; UGPA and 1L rank, 0.740; index and 1L rank, 0.759; LSAT and 3L rank, 0.730; UGPA and 3L rank, 0.733; index and 3L rank, 0.744).

[34] Baiyin Yang & Diaopin Rosa Lu, *Predicting Academic Performance in Management Education: An Empirical Investigation of MBA Success*, 77 J. EDUC. FOR BUS. 15, 16 (2001).

[35] *Id.* at 18.

[36] *Id.* at 19.

[37] *Id.*

[38] William D. Henderson, *The LSAT, Law School Exams and Meritocracy: The Surprising and Undertheorized Role of Test-Taking Speed*, 82 TEX. L. REV. 975 (2004).

[39] *Id.* at 1030 ("[Law school] reliance on time-pressured exams exerts a significant … effect on the relative importance of the LSAT [over UGPA] …. [D]ifferences in test-taking speed rather than reasoning ability may account for why the LSAT … emerges as a stronger predictor.").

[40] *Id.* at 1044.

[41] *Id.* at 979 (surveying literature and collecting citations).

broader mix of take-home exams, papers, and clinical-and-simulation performances as "arguably more reflective of the systemic time pressure found in the actual practice of law" than traditional in-class tests.[42]

Most critically, no studies control for data on many other important traits, such as college quality or major, work experience type or duration, or criminal or disciplinary records. A more rigorous major or college might predict law school success, whether because grades in a more rigorous curriculum are more reliable predictors, because the same 3.3 UGPA (for example) is a more impressive accomplishment in a more rigorous curriculum, or both. One study a legal writing professor conducted, of her 538 students over 16 years, found that students' majors do make a difference: economics majors earned the best legal writing grades, with double-majors and those with M.B.A.s also performing above-average.[43] However, that study was unpublished, did not did not control for other factors, and featured modest subgroup sizes (*e.g.*, 16 economics majors);[44] thus, possibly the higher-performing economics majors just had higher LSATs, UGPAs, or college quality.

In sum, by not controlling for other predictors, LSAC's and other studies leave unknown the predictive validity of their findings on LSAT and UGPA. To be sure, no study can control for all influences on LGPA: some data are unavailable; other factors (*e.g.*, motivation) are not reducible to the sort of binary or continuous variables susceptible to regression analysis; still other factors that affect law student performance, such as major events in the life of a student, are too individualized to be a part of any statistical model. Thus, no regression can control for all factors that predict LGPA; the best any study can do is to include reasonably available data that measures, or serves as a proxy for, as many of the truly critical student qualities as possible – an effort detailed, as to this study, in the methodology section below.

B. Learning Strategies, from Reading Styles to Professional Orientation

Law schools frequently do assess students' personal and professional qualities, not just their numbers – yet almost no studies examine how personal or professional qualities actually predict law school success. Two helpful studies by Leah Christensen document the importance of a few key factors and argue more broadly to take personal and professional qualities seriously in assessing student potential.

In arguing for the importance of legal skills training, Christensen found that law school class rank was statistically significantly correlated with not only high lawyering skills class grades, but with being a "mastery-oriented" learner focused

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[42] *Id.* at 1044.

[43] Karin Mika, *Do Undergraduate Majors Correlate Highly with Success in Legal Writing Classes?*, at 27-28, 35 (2010) (unpublished study) (on file with authors) (summarizing that the sole categories in which students had above-average grades were "those with economics majors, those with double majors, and those with advanced degrees, and, more specifically MBAs").

[44] *Id.* at 32.

on learning something valuable,[45] and in contrast was not significantly correlated with being a "performance-oriented" learner focused on academic success for its own sake.[46] Correlating 157 law student responses to a learning goals survey with academic variables, including class rank, LSAT score, UGPA, and lawyering skills grades, the study found as follows: class rank positively correlated with lawyering skills grades (r=0.57), but less so with UGPA (r=0.46), and even more weakly with LSAT (r=0.23).[47] The study also found class rank was positively correlated with being a "mastery-oriented" learner[48] but not with being a "performance-oriented" learner.[49]

Another Christensen study found different legal reading strategies correlate with high first semester grades.[50] Among 24 students, high-performance and low-performance groups did not significantly differ in average LSAT or UGPA,[51] but different reading styles dominated each group. The latter spent the most time on basic "default" reading strategies: paraphrasing, re-reading, noting certain structural elements of text, underlining text, and making margin notes.[52] The former made heavier use of two more critical reading strategies: "problematizing" strategies of purposefully asking themselves questions, making predictions, and hypothesizing about meaning; and "rhetorical" strategies of moving through the text in an evaluative manner or by synthesizing with the reader's experiences.[53]

Christensen's findings evidence the value of positivity, emotional intelligence, work ethic, and learning styles – theories that abound but have not been proven as to law school grades. Yet Christensen's and other studies do not control for other variables, leaving a real possibility that the key variables are just proxies for other qualities. Perhaps older students with real-world experience are more "mastery-oriented" than those just out of college, whose recent focus on grades makes them "performance oriented"; if so, then the key predictor is work experience, not "orientation." Perhaps those with better reading strategies just did more recent reading due to majoring in (for example) history or starting law school right after college; if so, the key predictor is less "strategy" than quantity of recent reading. And the finding that lawyering skill grades correlate with LGPA may show not

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[45] Leah M. Christensen, *The Power of Skills: An Empirical Study of Lawyering Skills Grades as the Strongest Predictor of Law School Success*, 83 ST. JOHN'S L. REV. 795, 799, 806 (2009).

[46] *Id.* at 800, 804.

[47] *Id.* at 805. Where "r" is the correlation coefficient.

[48] *Id.* at 799, 806.

[49] *Id.* at 800, 804.

[50] Leah M. Christensen, *Legal Reading and Success in Law School: An Empirical Study*, 30 SEATTLE U. L. REV. 603, 604 (2007).

[51] *Id.* at 615.

[52] *Id.* (LP students spent a mean time of 77.48% engaged in default strategies, 12.54% in problematizing strategies, and 9.56% in rhetorical strategies).

[53] *Id.* at 609-610, 625 (HP students spent a mean time of 21.43% engaged in default strategies, 45.70% in problematizing strategies, and 32.87% in rhetorical strategies).

that particular student types do well; it may show just that good students perform equally well in skills and other classes. Multivariate analyses simultaneously examining all available data could distinguish between factors Christensen notes and other factors.

C. Emotional Intelligence

Research outside of law indicates that IQ-like raw intelligence may predict academic success, yet poorly predict job or relationship success.[54] The reverse may be true of emotional intelligence (“EQ”), or "social intelligence": ability to recognize and manage emotions, as well as see and care about impacts on others.[55] One study on MBA graduates found that businesses look less for IQ and more for EQ traits, such as initiative, communication ability, and interpersonal skills.[56] Another study found that roughly half of job performance relates to EQ.[57] And yet another study examined showed that student’s background, interests, hobbies and typical behaviors in a wide variety of academic and life situations positively affect performance.[58] Notably, EQ can improve,[59] making it not a purely endogenous predictor, but a trait learnable from training or experience in roles requiring emotional awareness. These studies support Kenneth Kleppel's argument that lawyer intellectual and professional skills are overvalued compared to EQ.[60] Lawyers have enough intellect to pass law school and bar exams, and most gain needed skills early in their careers – but they vary widely in EQ,[61] which can help them in several ways: dealing with emotions like anxiety and anger; making them leaders; and improving how clients or juries view them.[62]

While there is solid theory and data on the importance to *work* success of EQ, and of related traits such as leadership, maturity, and discipline, there is less solid data on the importance of these traits to *academic* success.[63] Work, especially

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[54] Carl A. Leonard, *Chapter 3. Leading the Law Firm, in* HILDEBRANDT HANDBOOK OF LAW FIRM MANAGEMENT (2012).

[55] Gretchen Neels, *The EQ Difference*, 28 LEGAL MGMT. 44, 46 (2009).

[56] *Id*. at 46.

[57] ADELE B. LYNN, THE EQ INTERVIEW: FINDING EMPLOYEE WITH HIGH EMOTIONAL INTELLIGENCE (2008).

[58] Neal Schmitt et al., *supra* note 32 (showing that biographical data positively predicts undergraduate performance).

[59] *Id*.

[60] Kenneth Kleppel, *Emotional Intelligence is Key to Success*, 2007 OHIO LAWYER 1, 1 (2007).

[61] *Id.* at 1.

[62] *Id.* at 2-3.

[63] Marjorie M. Shultz & Sheldon Zedeck, *supra* note 31; For a discussion of non-cognitive factors explaining academic performance in an undergraduate context, *see* Neal Schmitt et al., *supra* note 32 (concludes that Results indicate that the primary predictors of cumulative college grade point average (GPA) were Scholastic Assessment Test/American College Testing Assessment (SAT/ACT) scores and high school GPA (HSGPA) though biographical data and situational judgment measures added incrementally to this prediction); and For a discussion of non-cognitive factors explaining academic performance in an medical context, *see* Lievens and

lawyer roles requiring client contact, ability to persuade, and resilience under stress, likely places a premium on EQ and related traits. While students likely do better by managing emotions and understanding others as well, little evidence proves so.

In sum, the broad theoretical, and limited empirical, work on beyond-the-numbers soft skills and traits is valuable – but further study, especially multivariate analysis, is needed to assess their impact on law student grades. No study can code thousands of students' personal traits, of course; this study attempts to code for various experiences viewable as proxies for personal traits, such as having work experience versus attending law school right after college (a possible proxy for maturity), college leadership roles (a proxy for EQ), a criminal or disciplinary record (also a proxy for maturity, as well as for impulse control), and an improving GPA during college after a lower starting GPA (a proxy for resilience, in the sense of ability to improve after suffering a setback in an important endeavor).

III. METHODOLOGY

A. The Data Set

Following is how the authors procured and coded their data – a lengthy process that made this Article's empirical analyses possible. The working hypothesis was that information in students' law school applications and academic records can help predict their future success as law students. For each of the over 1400 students in the University of Colorado Law School and Case Western University Law School graduating classes of 2008-2011, we collected the following: (1) data from the original 2005-2008 law school applications on their college, employment, extracurricular, and criminal/disciplinary records; (2) data from law school and university registrars on their law school courses, grades, and activities; and (3) data from law school career services offices on their bar passage and post-graduation employment. Most of the data in categories (2) and (3) are for future study of employment and bar outcomes, so the focus below is category (1): applicant data.

We collected data from the 2005 to 2008 applications received by the University of Colorado Law School or Case Western Law School from those matriculating to join the graduating classes of 2008 to 2011: the basic application LSAC collects and distributes to each law school; the transcript and semester-by-semester UGPA report that LSAC compiles and distributes to each law school; the resume that nearly every applicant submits; and any other materials that flesh out details in the application.

Because reviewing and entering this data required reviewing each individual

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Sackett (2012), *The Validity of Interpersonal Skills Assessment via Situational Judgment Tests for Predicting Academic Success and Job Performance,* Journal of Applied Psychology, vol. 97, 460-468.

application, the authors, and those they employed to assist, spent several hundred hours on that review and data entry: opening each applicant's folder; reviewing the information; discussing any ambiguous or unclear data so the authors could decide how to code such data; and entering the data into a spreadsheet. All such data review and entry was either conducted by, or supervised on-premises by, one of the authors; *i.e.*, no data was evaluated or entered without one author present for resolving any ambiguities. The admissions data entry was on-site at each law school,[64] because the paper files were voluminous and contain sensitive data that had to remain secure.[65]

We created our database by entering the following information from each application: (1) LSAT score (the highest if there were multiple); (2) UGPA; (3) the median LSAT score of those at the college from which the student graduated ("LCM"), as a measure of college quality; (3) college major; (4) college graduation date; (5) whether UGPA rose materially during the final undergraduate semesters (yes=1, no=0); (6) significant college leadership roles (yes=1, no=0); (7) attainment of a graduate degree (yes=1, no=0); (8) a significant criminal or college disciplinary record, *i.e.*, more serious than an "open alcohol container" infraction (yes=1, no=0); (9) number of years between college and law school; (10) total number of years employed before law school; (11)-(16) number of years employed in each of six categories of employment (each is listed and defined below); (17) number years of substantive work experience, *i.e.*, more substantial than temporary or part-time work; (18) a written summary of the employment experience;[66] (19) state of residency as of the application date; (20) year of birth; (21) whether the student identified as having any nonwhite ethnicity (yes=1, no=0); (22)-(25) whether the student identified any nonwhite ethnicity (African American; Hispanic/ Latino; Asian / Pacific Islander; or Native American / Native Alaskan) (yes=1, no=0); (26) gender (male=1, female=0); and (27)-(33) whether the student had one of seven categories of college majors (each is listed and defined below) (yes=1, no=0).

Regarding the six categories of employment and seven categories of college majors: because there are too many particular jobs or majors to code each individually with a useful sample size, we grouped similar job types, and similar majors, into several broad categories – and the data entered were whether the student had each specified major or job category, as well as the number of years worked in each job category. We had the following categories of majors and jobs:

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[64] Moss traveled twice to Case Western, personally entering nearly half the data at that school and supervising Case Western staff who helped him enter the rest. Marks and Moss, combined, entered the vast majority of the Colorado data, with help from staff with whom they worked.

[65] Institutional Review Board ("IRB") review and each law school dean's consent were procured to access all data; the authors also signed a confidentiality agreement allowing reporting of the aggregated findings in this Article, just not disclosure of information on individual students.

[66] We did not create a separate variable based on this written summary; we just entered and maintained this data to document what kinds of work we classified in (11)-(16), the dummy variables for each of six categories of employment types.

- *Majors:* (1) psychology, sociology, anthropology, or religious studies; (2) economics, finance, or accounting; (3) political science, public policy, or government; (4) science, technology, engineering, or math; (5) fine arts, music, drama, or performing arts; (6) environmental studies, forestry, or ecology; and (7) liberal arts, history, any language, or philosophy.[67]
- *Jobs:* (1) teaching (any level, preschool to college); (2) legal (*e.g.*, paralegal, investigator, or law-related job such as child services); (3) business or management (financial work like accounting, investing, or banking, as well as sales work above that of a retail salesperson, such as securities work or managing an entire retail store); (4) science, technology, or medical (*e.g.*, scientist, lab technician, nurse, programmer, or engineer); (5) military (any branch); or (6) public service (*e.g.*, government, non-profit, or political work).

B. Regression Analysis of Admissions Criteria on Law School Grades

1. Hypotheses

By including as many variables as we could code, we set out to test various hypotheses that law student success can be predicted by (a) traits law schools value highly for applicant selection, (b) traits law schools appear to value less (if at all), and (c) traits the literature depicts as positive predictors of success. Specifically, we tested the hypotheses that high LGPA can be predicted by variables serving as metrics of the following personal qualities – with certain variables serving as possible proxies for more than one personal quality (*e.g.*, having work experience may be a proxy for maturity, but having no work experience, may be a proxy for being more able to acclimate to law school quickly). Table 1 outlines traits we hypothesized to predict law school success, followed by variables selected to test these hypotheses in the empirical analysis that follows. To be clear, some hypotheses included in Table 1 were exploratory, rather than testing a clear hypothesis or taking a particular side. For example, it is beyond the scope of this paper to review the literature on the effect of demographic factors on law school success, such as whether female students are more successful than male students.

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[67] Where a major did not fit cleanly into one category, either (a) no "1" was entered in any category (*e.g.*, for the few "recreation management" or "equestrian" majors), or (b) a judgment call was made about which category a particular major fit into (*e.g.*, "forestry" could be more a science major or more an environmental major, depending on the particular student's coursework). We coded 103 students with no major. When a student had a double major, we counted that major as well. There were 239 double-majors and six triple-majors.

Table 1: Hypotheses, and Variables Selected to Test Those Hypotheses

Traits Hypothesized to Predict Success	*Variables Selected to Test the Hypotheses*
1. Academic ability	• LSAT (& increasing/decreasing return variants) • UGPA (& increasing/decreasing return variants) • Certain majors (*e.g.*, STEM)
2. Rigorousness of prior Academics	• Having another graduate degree (& interactive term of graduate degree & being right out of college) • LCM (& increasing/decreasing return variants, as well as variant interacting LCM & UGPA) • Certain majors (*e.g.*, reading- or law-related)
3. Familiarity with the Educational setting	• Work experience as binary dummy variable (*i.e.*, no work equals attending law school right after college) • Certain work types (*e.g.*, law or public service)
4. Work ethic and Resilience	• Rising UGPA (generally, or only if right out of college) • High-UGPA/Low-LSAT profile • Leadership experience (generally, or only if right out of college)
5. Maturity and emotional Intelligence	• Lack of criminal/disciplinary record • Certain work types (*e.g.*, military or teaching) • Work experience length (*i.e.*, 1-4, 5-9, or 10+ years)
6. Demographic traits	• Gender • Various race/ethnicity self-identifications

NOTE: This table describes the hypotheses and variables used to test those hypotheses

2. Models

a. The Primary Regressions: Models 1 (LGPA) and 2 (1L GPA)

We specified two ordinary least squares ("OLS") regression models to test the above hypotheses. Our two primary models included the same independent variables as predictors, but with different dependent variables: *cumulative* law GPA ("LGPA") in Model 1, and *first-year* law GPA ("1L GPA") in Model 2. We explored both on the theory that some students may adjust more or less quickly to law school, so some variables may more strongly predict 1L GPA than cumulative LGPA. For example, consider law students with less, or less-recent, reading and writing exposure, such as science or finance majors (compared to history, political science, or English majors), or those several years removed from college. Such students may under-perform 1L year, being unfamiliar or rusty with heavy reading and writing – yielding subpar 1L GPA. But as they adjust to law school, or specialize in their chosen upper-level curriculum (*e.g.*, intellectual property or corporate transactions), their performances may disproportionately improve –

yielding improved LGPAs. This is just one example of how some talented students may need more time to adjust to law school – yielding subtle differences in predicting 1L GPA and cumulative LGPA.

We ran these two regressions, Model 1 and Model 2, using the entire data set, with 1419 observations and 28 independent variables; Table 2 in Section III displays the results. Among the independent variables, three are continuous variables and 25 are dichotomous (0/1) "dummy," variables. Table 4 in the Appendix provides the summary statistics for the variables in the dataset, while Table 9 provides means and variances for selected dummy variables. The means and standard deviations of the continuous variables in our study are as follows: LSAT (mean=159, std. dev.=5.30, range=133 to 178), UGPA (mean=3.43, std. dev.=0.35, range=2 to 4.11), LCM (mean=154, std. dev.=4.15, range=132 to 168), LGPA (mean=3.18, std. dev.=0.34, range=2.03 to 3.99), and 1L GPA (mean=3.08, std. dev.=0.41, range=1.87 to 4.0).

We were interested in the incremental effects of adding variables to the model instead of entering them all simultaneously. We ran six versions of each model to measure the effect of adding certain pre-determined groups of variables. For each set of regressions, we began by running a simple "base" regression model mentioned in the previous studies, with only the most obviously relevant predictors (*e.g.*, UGPA, LSAT, and LCM). While LSAT was used in its simplest form, we adjusted two variables, UGPA and LCM, after conducting robustness checks for nonlinear effects of LSAT, UGPA, and LCM.[68] We also checked for interactions between variables, such as whether UGPA mattered more at a stronger college,[69] but ultimately did not use most interaction terms because they

[68] We performed several tests to determine whether the effect of each continuous variable was linear or nonlinear. First, we tested whether LSAT, UGPA, and LCM had *consistently increasing or decreasing, rather than linear, returns*, by raising each to various powers above 1.0 (increasing returns) or below 1.0 (decreasing returns). For example, we replaced the LSAT variable with LSAT raised to various powers from 0.25 to 3.0, to see which was a stronger predictor. (We subtracted 130 from LSAT before raising it to any power, because 132 was the lowest LSAT in the data, and raising values from 132 to 178 to various powers would understate any nonlinearity, compared to a score starting just above 0.) Second, we tested for *discontinuities or sudden jumps* at particular levels, such as (a) that LCMs below a certain level may be especially bad (*i.e.*, that weak colleges may be not just incrementally worse, but worse by some nonlinear quantum, than average to strong colleges), (b) that UGPAs above a certain level (*e.g.*, some B+/A- level) might be especially strong plusses, or (c) that UGPAs below a certain level (*e.g.*, C+/B-) might be especially negative predictors. Third, as a catch-all test of any nonlinear effects we might not suspect, we used the Stata *fracpoly* command to obtain an estimate of any other nonlinear models that might fit the data better than the specific ones we hypothesized; ultimately, the *fracpoly* results yielded no other nonlinear model better than the models we ultimately chose on our own.

[69] To test whether college grades are better predictors when adjusted for college quality, we interacted UGPA with LCM (*i.e.*, replacing UGPA and LCM with UGPA multiplied by LCM); to test whether pre-law school academic traits – rising UGPA, college leadership, and having another graduate degree – are better predictors when limited to those attending law school right after college we replaced those three variables with an interaction between each and whether the

did not add any predictive power. Appendix Table 5 displays the simple LGPA regression under column 1a; Appendix Table 6 displays the simple 1L GPA regression under column 2a. Of note, the LGPA regression is based upon 1419 observations while the 1L GPA regression is based upon 1317 observations, because it excludes those who transferred to the school after spending their first year at another law school.

Not surprising, our results predicting 1L GPA, found in Table 6 column 1a, are typical of other results found by the LSAC in their analysis of the usefulness of LSAT as a predictor of 1L GPA. In a series of regressions using data from 152 unnamed schools over 2011 and 2012, LSAC estimated first year GPA from a combination of LSAT and UGPA.[70] The LSAC study shows that our two schools are "typical" in that the correlation coefficients between first year grades and the LSAT, UGPA, and a combination of LSAT and UGPA, respectively, in our study, are nearly identical to the LSAC study averages. The LSAC study reported these median correlations: First Year Average ("FYA") (a variable equivalent to our 1L GPA) and LSAT (r=0.35), FYA and UGPA (r=0.29), and LSAT and UGPA combined (r=0.47). Comparable to the LSAC study findings, our study found these median correlations: FYA and LSAT (r=0.37), FYA and UGPA (r=0.28), and LSAT and UGPA combined (r=0.39). Our results track the LSAC results, making our two schools "typical" for comparison purposes.

As far as 1L GPA is concerned, our correlations and R-square results generally track the LSAC findings. While the correlation coefficient gives us the strength of the linear relationship between the coefficients, squaring the correlation coefficient yields the coefficient of determination ("R-square"), which gives us the variation that can be explained by the linear relationship between the two variables. Their highest FYA and LSAT correlation (r=0.54), translates in an R-square of 0.29 while their lowest FYA and LSAT correlation (r=0.16), translates into an R-square of 0.03. The R-square values that we report in our study are not the highest R-square values that the LSAC study reports – but they are also not the lowest. They are closer to the averages that the LSAC study finds, making our schools 'typical'.[71]

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student had any work experience before law school. The sole interactive term that proved more powerful was rising UGPA for those with no work experience, *i.e.*, the interactive variable testing whether rising UGPA had a greater effect for those attending law school right after college.

[70] *See* Anthony, Lisa A., Dalessandro, Susan P., and Reese, Lynda M., *Predictive Validity of the LSAT: A National Summary of the 2011 and 2012 LSAT Correlation Studies*, Law School Admissions Council, LSAT Technical Report No. 13-03 (Nov. 2013), available at http://www.lsac.org/docs/default-source/research-%28lsac-resources%29/tr-13-03.pdf.

[71] *Id.* at 17. Two further points reveal why, perhaps, our R-square for regressions 1a are within the range of LSAC findings yet not on the high range of their findings. First, the LSAC study cautions that r-square values can vary greatly among schools due to wider distributions which

After running the initial "base" regression model using a combination of LSAT, UGPA and LCM, we successively re-ran the regression adding additional variables parsimoniously (*e.g.*, first adding ethnicity, then years of work experience, work experience type, college majors and other control variables, in that order). We inserted variables in groups because those variables had something intrinsically in common, we inserted them when we did because we had a sequence in mind. Admittedly, we expected the R-squared to grow as those variables reduced the overall variance; we expected the 'base' variables to remain strong and significant; and we expected that a variable that became significant would not lose its significance in subsequent models. Table 5 (Appendix) displays the additional LGPA regressions under columns 1b-1f; Table 6 (Appendix) displays the additional 1L GPA regressions under columns 2b-2f. (Columns 1f and 2f in Tables 5 and 6, respectively are the full models, reproduced and interpreted in Table 2, Section III, *infra*). In the LGPA regressions, we were surprised to find that '1-3 years of work experience' variable was significant in regression 2c but lost significance to '4-9 years of work experience' in the final model, 2f. Both variables 'tech employment' and 'art and music major' were negative and significant (albeit at the 10% level) in the final regression only. In the 1L GPA regressions, we were surprised to see that the variable '10+ years of work experience' was later replaced in significance by the variable '4-9 years of work experience". The 'teaching work experience' variable decreased in significance from the 1% level in regressions 2c-e, to 5% in the final regression, 2f.

In addition to the primary models noted above, we specify 3 additional models to explore additional questions. First, are there subtle differences between what predicts especially high and especially low grades? Second, who is the better bet, the high-UGPA candidate with a low LSAT, or the high-LSAT candidate with the low UGPA? We tackle each inquiry below.

b. The Quarter Regressions: Model 3 and Model 4

While the primary regressions examine what predicts LGPA and 1L GPA, Models 3 and 4 ("The Quarter Models") test for subtle differences between what predicts success and what predicts failure. Our hypothesis was that perhaps a certain negative trait predicts a very low LGPA, but its absence does not predict any difference between high and mid-range LGPAs, and the reverse could be true for a positive trait. To examine what predicts top-quarter ("Q1") or bottom-quarter ("Q4") LGPAs, we specified two logistic regression models.[72] Logistic regression

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will lead to lower R-squares, individual schools' variability of LSAT scores and UGPAs, the correlation between LSAT score and UGPA, and the amount of variability in the first year grades. Another factor to consider is that our study reports adjusted r-square, a value which is a lower (adjusted for the parameters) value than the r-square.

[72] The top-quarter subset included the top quarter of students at both law schools; the bottom-quarter subset included the bottom quarter of students at both law schools.

techniques are used when the dependent variable is dichotomous; in our case, the dependent variable was coded “1” if the student was in the specified quarter, else “0.” Thus, in Model 3, the dependent variable is membership in the top quarter; in Model 4, membership in the bottom quarter. We ran these regressions using the same independent variables used in Model 1; the results are in Appendix Table 7.

c. The Splitters Regression: Model 5

There is a recurring debate in the admissions world: if forced to choose between the two major numerical criteria, LSAT and UGPA, who is the better bet, the high-UGPA candidate with a low LSAT, or the high-LSAT candidate with the low UGPA? We specified a model to test whether students with either "splitter" – high-UGPA/low-LSAT or low-UGPA/high-LSAT – performs differently from the other type, or from non-splitters. Using only a dataset of splitters (733 observations) Model 5 uses OLS regression techniques to predict LGPA using all independent variables in the previous models, replacing the UGPA and LSAT variables with (a) an index combining LSAT and UGPA and (b) including an indicator variable for "mild splitters", students with a top-50% LSAT but bottom-50% UGPA and vice versa, coded "1" if the applicant fit into that profile, else "0." Since the dataset only contained splitters, the default category is the high-UGPA/low-LSAT profile. The Model 5 results are found in the Appendix Table 8.

For robustness, we ran two additional OLS models. In the first regression we used a dataset of "extreme splitters", students with a top-25% LSAT but bottom-25% UGPA, and vice-versa to test whether the high-LSAT but low-UGPA performs differently than the high-UGPA but low-LSAT profile. Next, we ran a second model including all 1435 observations, the index again in place of LSAT and UGPA, and a dummy variable for the high-UGPA/low-LSAT splitters to test whether the *high-UGPA*/low-LSAT splitters did worse or better than non-splitters. Table 4 in the Appendix also details the sample sizes in these groups. A more lengthy discussion of the splitter regressions is found *infra*, Section IV.D.

d. The Variance Analysis

Finally, following the five regression models, we examined whether LGPA had greater variance for any group represented by one of the dichotomous dummy variables, *e.g.*, each cluster of majors, and each cluster of job types. A finding that a group had higher variance than other similarly-sized groups could hint that the group contains high-risk/high-reward candidates, or that the group is a heterogeneous mix requiring closer individual scrutiny of individual members.

IV. KEY RESULTS AND INTERPRETATIONS

A. Caveats: Limitations on Modeling Law Student Performance

This Article's core findings are from the Model 1 regressions exploring what predicts LGPA. The results of the “Quarter Regressions” and “Splitter Models” further refine those findings.[73] Before detailing the results, three key caveats and limitations of our regression models warrant mention, to avoid overstating the findings and to note possible biases in the results.

First, we could not code for many variables that may be valuable as predictors of law school performance. Writing ability is likely an important predictor, but one that was not feasible to enter as coded data. Reading and grading the writing in over 1400 applications with sufficient consistency would have been a possibly insurmountable challenge, but more importantly, true writing samples were not consistently available. Applicants' personal statements are commonly edited by others, as evidenced by how (in the authors' experience reading thousands of law school applications) the unedited handwritten LSAT essays are far less strong, grammatically and stylistically. Yet a sizeable minority of the handwritten LSAT essays are illegible, either because of bad handwriting or because they are written in often-smudged pencil. We similarly could not code directly for personal qualities and backgrounds that could bear on law school success, such as family educational and socioeconomic background and personal qualities such as resilience, optimism, etc. Even if we could code hints of such factors reliably from subjective indicia in personal statements, many applicants do not mention or hint at such factors (*e.g.*, some mention family economic and educational background, but many do not, and some mention obstacles they overcame, while others do not), so the data would be too incomplete to be entered into a regression for most or all of the population. However, we tried to keep these possibly important but uncoded qualities in mind in interpreting our results, because – as detailed below – the findings hint that certain variables may be proxies for uncoded qualities such as work ethic, resilience, etc.

Second, though the populations of the two law schools vary, they do not cover the entire range of law students. For example, the population in our data set contains a wide range of LSAT scores: the bottom 5% (*i.e.*, about 72 students) are at or below 150, while the top 5% (also about 72 students) are at or above 168. Yet there are law schools at which many more students have LSAT scores in the 140s or in the 170s. Thus, while we chose our two schools to maximize representation of the low 150s to mid-160s LSAT range that is most common, our results may be less generalizable to the very top and bottom of the law student population.

Third, there is possibly a bias in favor of the high-LSAT/Low-UGPA splitters over the high-UGPA/Low-LSAT splitters. There is some evidence of this in that our data on “mild splitters” – students with top-50% LSAT but bottom-50% UGPA or vice versa contained more high/LSAT splitters. Law schools may bias admission toward one splitter category to improve their LSAT and UGPA medians.

Finally, we face an inherent limit in statistically modeling a population that is not a random sample. Law students are not a random sample of law school

[73] All models were run using the Stata, version 12, statistical software.

applicants, but the subset deemed worthy of admission – which biases our findings mainly toward understating the effect of certain traits.[74] For example:

- those with the worst negative discipline or criminal records are denied admission, so our population includes only less negative records – biasing our study toward finding a record has less (or no) effect; and
- among applicants with low UGPA or LSAT scores, only those with enough other positive qualities are admitted, so our population includes only the subset of low-scorers with other positives – biasing our study in favor of finding less (or no) effect of a lower score.

Formally, our data set features Berkson's bias, a form of selection bias: by analyzing only the subset of applicants who matriculated, we obtain only conditional estimates (of the subset who met the condition of being admitted), not unconditional estimates (of how the entire applicant population would perform). This form of selection bias is common in many fields, such as criminal or civil litigation, where analyses of trial outcomes consider only a conditional subset – cases not resolved before trial (by plea, settlement, dismissal, etc.).[75] Because the problem is a bias due to an omitted variable (the odds of being selected into the population being examined), the Heckman model can sometimes correct for the bias, by adding a second step to the regression: first, a "selection function" estimates the odds an individual becomes part of the population (here, the odds of admission); then, that estimate is inserted into the "response function" analyzing the effect of each variable (here, LGPA), to correct for the fact that some individuals were more likely to be selected than others.[76] Yet the Heckman model proved not to be a feasible corrective here, because it requires fuller data than we could procure on all potential population members, and because it requires strict conditions which cannot be met in this study.

Ultimately, lacking counter-factual data on how non-admitted students would have performed if admitted (*e.g.*, those with especially negative records, or low scores, not mitigated by other positives), we simply must note that our study, like other studies on matriculants[77], is biased toward under-stating the effect of most variables. Ultimately, the bias may not be substantial for two reasons.

[74] LSAC also acknowledges this bias in their studies of law student performance. *See* Anthony, Lisa A. et al., *supra* note 70 at 12-13.

[75] *See, e.g.*, Shawn Bushway, Brian D. Johnson, and Lee Ann Slocum, *Is the Magic Still There? The Use of the Heckman Two-Step Correction for Selection Bias in Criminology*, 23 J. OF QUANTITATIVE CRIMINOLOGY 151 (2007).

[76] James Heckman, *Sample Selection Bias as a Specification Error*, 47 ECONOMETRICA 153 (1979); James Heckman, *Dummy Endogenous Variables in a Simultaneous Equation Model*, 46 ECONOMETRICA 931 (1978).

[77] *See* Anthony, Lisa A. et al., *supra* note 70 at 17 (In their study on LSAT validity, LSAC notes, "Correlations obtained from matriculated students tend to underestimate the true validity of the test. Even so, they are the best information we have available, and even as underestimates they are quite reliable").

First, we did find many variables to be highly significant predictors of 1L GPA and LGPA – likely because the two key predictors, LSAT and UGPA were not negatively correlated. The worst-case scenario for bias would have been if LSAT and UGPA had been negatively correlated. If, among those admitted with a high LSAT, those with a low UGPA were more likely to matriculate (because those with a high LSAT *and* UGPA receive more and better admission offers), then the matriculants with a high LSAT (a positive predictor) would have a disproportionately low UGPA (a negative predictor); to the extent that a high LSAT is usually accompanied by a low UGPA, then LSAT would not appear to be as positive a predictor as it truly is. And vice-versa: if those who matriculated with a high UGPA tended to have lower LSAT scores, then UGPA would not appear to be as positive a predictor as it truly is. Yet in our data set, LSAT and UGPA were *not* negatively correlated.[78] Thus, the data do not support a key feared source of bias: that those who matriculated with one positive predictor probably were worse in other ways, leaving the effect of that positive predictor understated.

Second, the relative predictive power of LSAT and UGPA that we found made intuitive sense, was consistent with findings in other studies, and should not be affected by selection bias. LSAT is stronger at predicting first-year grades (the correlation between 1L GPA and LSAT, and 1L GPA and UGPA, are 0.36 and 0.27, respectively); UGPA is slightly better at predicting cumulative grades (the correlation between LGPA and LSAT, and LGPA and UGPA, are 0.28 and 0.29, respectively). While these correlations might be higher if it were feasible to examine how the full applicant pool (including rejected applicants) would have performed, their relative values would not likely change. Corroborating this interpretation is an LSAC study of 152 law schools, in which correlations for a full applicant pool did prove higher than those for a matriculant pool, but the relative predictive power of LSAT and UGPA as to first-year grades remained the same.[79]

B. The Primary Regressions: Predicting Cumulative LGPA (Model 1) and 1L GPA (Model 2)

What variables predict higher law school grades? Below, Table 2 is the full set of results detailing each variable's OLS coefficient and significance; Table 3 summarizes the magnitude of each significant variable's correlation with LGPA; and Table 9 provides variances and standard deviations for selected dummy variables.

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[78] LSAT and UGPA had a positive and modest correlation of 0.187. *See also* Anthony, Lisa A. et al., *supra* note 70 at 18 (in a study of 152 law schools between 2011 and 2012, finding the average correlations between LSAT and UGPA are close to zero and range from -0.45 to 0.24, suggesting that a number of law schools employ a compensatory admissions model in which a high LSAT score compensates for a low UGPA, or vice-versa).

[79] *Id.* at 18 (to estimate the correlation coefficients with first year law school grades for the entire applicant group, a statistical adjustment for restriction of range was applied to the data that are available for the group of students who matriculate; the applicant pool correlations are adjusted based on Pearson-Lawley formulas).

Unsurprisingly, factors predicting 1L GPA (Model 2) were much the same: 1L GPA is a subset of LGPA, so variables predicting 1L GPA likely impact LGPA, and qualities predicting 1L grades also likely predict 2L-3L grades. We hypothesized and found only subtle differences between the 1L GPA and LGPA predictors: some factors predict slower acclimation to the reading, writing, and legal analysis demands of law school (*i.e.*, worse 1L than cumulative LGPA); others predict faster acclimation (*i.e.*, better 1L than cumulative LGPA). The adjusted R-squared is 0.263 for Model 1 and 0.279 for Model 2, meaning the predictor variables explained 26.3% of all variation in LGPA, and 27.9% of all variation in 1L GPA, among law students.

Of note, we ran an OLS specification identical to those used above, only this time we included 1L GPA to predict LGPA. Now, because 1L GPA is part of LGPA, those two variables are highly correlated (r=0.88) and we expect that 1L will be a strong and significant predictor of LGPA. Using 1315 variables to predict LGPA, as expected, the adjusted R-squared in that regression is 0.7914 and the coefficient for 1L GPA is 0.688, positive and significant at the 1% level. Among our three highest Model 1 and Model 2 predictors, LSAT, UGPA and LCM, only two are significant in this regression. The coefficient for UGPA is 0.083, positive and significant at the 1% level and the coefficient for LCM is 0.001, positive and significant at the 5% level. LSAT is negative but not significant. Among all other variables, the data suggests that Asian Americans are less likely to get higher LGPA (coefficient was -0.0544, significant at the 1% level), and those with STEM or EAF backgrounds are more likely to get higher LGPA (coefficients were 0.0340 and 0.0290, respectively, both at the 5% significance level). While the goal of this study is not to predict LGPA using a component of LGPA, this specification does reveal one interesting point about the relationship between first year grades and third year grades. While the data supports the finding that students who do well in their first year do well overall, the same can be said for the bottom of the class – students who do not do well in their first year do not do well overall. However, the 1L GPA predictor is not perfect. It may explain 79% of the variance but it does not explain 100% of the variance, revealing that interventions after the first year can potentially make a difference in increasing LGPA.

Table 2: OLS Regression Results for Model 1 (Dependent Variable: Cumulative LGPA) and Model 2 (Dependent Variable: First-Year LGPA)

Variables	*Model 1: Cumulative Law School GPA (LGPA)*	*Model 2: First Year Law School GPA (1L GPA)*
Traditional factors		
Law School Admissions Test (LSAT)	0.016*** (9.31)	0.030*** (12.63)
Adjusted LSAT College Median (LCM)	0.003*** (3.55)	0.004** (2.98)
Adjusted Undergraduate GPA (UGPA)	0.272*** (12.44)	0.328*** (11.22)
Ethnicity		
African American	-0.155*** (3.77)	-0.170** (3.35)
Latino/a	-0.148*** (3.29)	-0.148** (2.52)
Asian American	-0.154*** (5.81)	-0.130*** (3.77)
Native American	-0.173** (2.28)	-0.188** (1.97)
Employment duration		
1-3 years	0.032 (1.47)	0.032 (1.16)
4-9 years	0.109** (2.88)	0.110** (2.49)
10+ years	0.014 (0.25)	0.081 (1.11)
Employment type		
Teaching	0.082+ (2.20)	0.086+ (1.80)
Legal	0.022 (0.69)	0.015 (0.35)
Business	-0.023 (0.75)	-0.025 (0.61)
Technology	-0.05 (1.55)	-0.077+ (1.85)
Military	-0.119+ (2.25)	-0.231** (3.43)
Public Service	0.043 (1.17)	0.068 (1.44)
College major		
Science, Tech., Engineering, Math (STEM)	0.066** (2.65)	0.061+ (1.90)
Economics, Accounting, Finance	0.058** (2.30)	0.032 (0.97)
Psychology, Sociology, Anthropology	-0.006 (0.30)	0.011 (0.38)
Art, Music, Drama	-0.038 (0.80)	-0.084+ (1.33)
Environmental Sciences	0.022 (0.42)	0.012 (0.17)
Liberal Arts, History	-0.001 (0.08)	0.016 (0.70)
Other factors		
No work experience & rising college GPA	0.033 (1.45)	0.053+ (1.82)
Criminal History	-0.119** (3.39)	-0.137** (2.99)
Graduate Degree	0.030 (1.22)	0.037 (1.16)
University of Colorado Law Student	-0.209*** (10.12)	-0.225*** (8.33)
College leadership	0.018 (0.67)	0.019 (0.51)
Gender male	0.014 (0.89)	0.015 (0.72)
Constant	-0.821** (2.70)	-3.470*** (8.21)
Adjusted R^2	0.26	0.28
Observations	1419	1317

NOTES: Absolute value of z-statistics in parentheses. +p<0.10; ** p<0.05; ***p<0.01.

Table 3: Summary of Magnitudes of Variable Correlations with LGPA (Model 1)

Positive Predictors	*Negative Predictors*	*Non-Predictive (No Correlation w/ LGPA)*
LSAT*** (best fit: linear) • +1 LSAT pt. ≈ +0.02 LGPA	**Negative Disciplinary or Criminal Record**** • Neg. Rec. ≈ $-7^{1}/_{3}$ LSAT	**Work Duration**: 10 or more years.
UGPA*** (best fit: increasing returns) • if UGPA<3.4: +.08 UGPA ≈ +1 LSAT • if UGPA≥3.4: +.04 UGPA ≈ +1 LSAT (consistent across all college qualities)	**Work Type**: Military+; Sci/Tech (not sig.: p=.110) • Military ≈ $-7^{1}/_{3}$ LSAT • Sci/Tech. ≈ -3 LSAT	**Work Type**: All other than teaching & military (*i.e.*, law, sci./tech., business, public service)
LCM*** (best fit: decreasing returns) • +1 LCM pt. ≈ +0.2 LSAT • LCM<152 ≈ additional -1 LSAT	**Demographics**: Person of Color Self-ID (** to ***) • Person of Color Self-ID ≈ -9 to -10 LSAT (but partly b/c a portion enter w/ lower scores)	**Majors**: All other than STEM/EAF (*i.e.*, social or political sciences; history; liberal arts; fine arts; environment)
Major: STEM**; EAF** • STEM major ≈ +4 LSAT • EAF major ≈ +3½ LSAT		**Demographics**: Gender (No discernible M/F difference)
Work duration: 4-9 yr.** • 4-9 yrs.' work ≈ +6½ LSAT		**Prior Graduate Degree** (Any)
Work type: Teaching* • Teaching ≈ +5 LSAT		**Major College Leadership Role** (Any)
UGPA rising ≥ 0.3, if enter law school right after college (not sig.: p=0.126) • Rising GPA ≈ +2 LSAT		

NOTES: +p<0.10; ** p<0.05; ***p<0.01.

Interpreting the Model 1-2 OLS regression coefficients is straightforward. The coefficient for each independent variable reflects both the strength and type of relationship the explanatory variable has to the dependent variable. When the sign associated with the coefficient is negative, the relationship is negative; conversely, when the sign associated with the coefficient is positive, the relationship is positive. The more positive or negative the coefficient, the more it predicts LGPA.

The interpretations of the coefficients vary depending on the type of variables in the study. Some variables are continuous, comprised of numbers along a spectrum (*e.g.*, UGPA, LSAT, LCM, and number of work years), while others are dichotomous (*e.g.*, a "yes" or "no" – coded for each work type, major, or criminal/disciplinary record). For a dichotomous variable, "1" means having the trait and "0" means not having it, so the coefficient reveals how much LGPA rises or falls when that trait is present. For a continuous variable, the coefficient represents the expected change in the dependent variable for a one-unit increase or decrease in the associated independent variable, holding all other variables constant. So the coefficient is the LGPA difference predicted by a one-unit difference in the variable, holding all other variables constant – *e.g.*, the LSAT coefficient shows how much LGPA rises with each one-point LSAT rise. A few continuous variables are *nonlinear*, to test for increasing or decreasing effects as the variable rises, or for interactions with other variables; interpreting those coefficients is less intuitive and will be discussed below as needed. The statistical significance of each variable's correlation with LGPA is noted in Tables 2-3 by asterisks: three asterisks (***) is the strongest statistical relationship, a 1% or lower chance the relationship resulted from chance variation; two (**) means a 5% or lower chance; a (+) means a 10% or lower chance (typically considered barely significant); no asterisk means a variable is not significantly correlated with LGPA. In Table 2, the results in bold highlight statistically significant results.

One novelty of this study is the way that it presents the key results in two ways. Like most traditional empirical studies, it presents the results based on coefficients and relative magnitudes. To explain the results more intuitively, we also present results in comparison to LSAT points. Because Model 1 uses a linear regression, the coefficient on each variable is the effect on LGPA of a one-unit change in the that variable (*e.g.*, the .016 coefficient on LSAT means each extra LSAT point predicts an extra 0.016 in LGPA, holding other factors constant). That also means each variable's effect can be compared – and here, comparison to LSAT points is an intuitive way to illustrate the relative power of each variable that proved significant (*e.g.*, the coefficient on teaching experience, 0.082, is just over five times the LSAT coefficient, 0.016, so it is roughly equivalent to five LSAT points). Table 3 lists of the number of LSAT points to which each other significant variable is equivalent.

The following nine subparts of this section detail the key results.

1. LSAT: 1 LSAT Point ≈ 0.016 LGPA

LSAT is, as in all prior studies, a significant LGPA predictor. The coefficient is 0.016, positive and significant at the 1% level. Roughly, each additional LSAT point predicts a 0.016 LGPA rise (the coefficient on LSAT, measuring the effect on LGPA of each LSAT point). This magnitude is large enough to make a real difference, because candidates typically vary by many points; a 6-point LSAT gap between two candidates predicts a 0.1 LGPA gap – a material difference in class standing.

Though LSAT is a significant predictor, for three reasons its validity as an admissions criterion is more modest than is implied by how heavily schools weight it in admission and scholarship decisions.[80] First, the magnitude of the predictive power of LSAT is modest compared to how heavily schools weight LSAT scores.

[80] *See supra* Part III(B)(2)(c) (noting evidence various law schools weight LSAT far more than UGPA).

A 6-point LSAT difference is enough to make a dispositive difference in where one attends law school and whether one receives a six-figure scholarship – but even that large an LSAT gap really predicts only a modest 0.1 difference in LGPA. Further, LSAT is just one valid predictor among many: as detailed below, many other valid predictors each are the equivalent of a 2-7 point LSAT difference.

Second, changes in LSAT do not appear to have increasing or decreasing returns; an X-point difference between a low and very low LSAT predicts the same as an X-point difference between a high and very high LSAT.[81] Thus, contrary to some common assumptions, a "cutoff" driven by fear of an especially low LSAT is unsound: the difference between a 147 and a 152 is the same as the difference between a 157 and a 162; and as noted below, various positive predictors each are akin to having several additional LSAT points, so even an LSAT score 12-15 points below a school's median can easily be counteracted by enough other positives.

Third, roughly half the LSAT's predictive power may be for the non-substantive reason William Henderson hypothesized: most law school exams and the LSAT are roughly three-hour, timed, in-class tests, so the LSAT is predictive partly as a mere measure of comfort and experience taking such exams. Henderson so concluded in finding that the LSAT predicts in-class test grades better than other grades (research papers, etc.), and our regressions provide further support for that conclusion: the LSAT is nearly twice as predictive of 1L GPA as it is of cumulative LGPA. Table 3 illustrates that each additional LSAT point predicts a rise in 1L GPA of 0.030 (significant at the 1% level). If the LSAT purely tested brainpower, it would not lose half its predictive power after 1L year. Because 1L year amounts to an in-class exam boot camp, students' test-taking skills converge by their 2L and 3L years – when the LSAT loses about half its predictive power. Thus, while the LSAT helps predict LGPA, as much as half its predictive value is not an aptitude test, but a non-substantive measure of ephemeral differences in test-taking comfort and experience.

In sum, these findings – on the modest magnitude of LSAT's predictive power, and on how half of that predictive power may be for a non-substantive reason – call into question the heavy reliance on LSAT in law school admissions, law school scholarship decisions, and law school rankings. To be sure, it is understandable that law schools feel compelled to rely heavily on LSAT: as Part

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[81] This linear LSAT-LCM model was a better fit for our data than other models we explored, including (a) a consistently increasing-returns LSAT-LGPA relationship (*e.g.*, an exponent above 1.0 on LSAT), (b) a consistently decreasing-returns LSAT-LGPA relationship (*e.g.*, an exponent below 1.0 on LSAT), (c) models hypothesizing a discontinuous effect at especially high or low levels of LSAT (*e.g.*, that a drop below a certain level such as 150 or 152, or a rise above a certain level, such as 165 or 167, has a disproportionate impact), or (d) models allowing a different coefficient on bottom-quarter and top-quarter LSAT scores (i.e., replacing LSAT with an interactive terms of LSAT multiplied by whether LSAT was in each quarter), to test whether to the effect of additional LSAT points was different in the mid-range than at the extremes (and we found no material difference in the LSAT coefficient for any quarter).

II(A) details, LSAT is a dominant driver of changes in law schools' rankings, to a far greater extent than UGPA (which the rankings consider, but to a lesser degree) and other factors wholly ignored by rankings' limited set of variables for student quality (*e.g.*, students' college quality, majors, and work experience). This Article's findings simply indicate that the goal of accurately assessing applicant potential does not support the substantial weight on LSAT that rankings incentivize law schools to accord.

2. UGPA: Increasing Returns; 0.03-0.06 UGPA ≈ 1.0 LSAT Point

UGPA significantly predicts LGPA, but increases in UGPA have greater effect at higher levels of UGPA. The coefficient is 0.272, positive and significant at the 1% level. The 0.272 coefficient on UGPA means that each full-point UGPA rise (*e.g.*, 2.0 to 3.0) predicts a 0.27-point LGPA rise, or (identically) each extra hundredth of a point of UGPA predicts a 0.0027 LGPA rise. But the UGPA variable that best fit the data was a doubling of that effect when UGPA is above 3.4 (*i.e.*, just over the B+ level, the mean at most colleges); above 3.4, each extra hundredth of a point of UGPA predicts a 0.0054 LGPA rise.[82]

The most intuitive understanding of this magnitude may be to compare it to the effect of LSAT: each 0.06 rise in UGPA is akin to 1 extra LSAT point, but above 3.4, the effect doubles, so each 0.03 rise in UGPA is akin to 1 extra LSAT point. Thus, the difference average and weak UGPA is material (e.g., 3.0 versus 3.3 is akin to 5 LSAT points), but not as powerful as the difference between good and elite UGPA (*e.g.*, 3.5 versus 3.8 is akin to 10 LSAT points).

Compared to prevailing models deeming LSAT a better predictor than UGPA, we find that UGPA is more powerful – at least when, as here, the analysis controls for factors that moderate the effect of UGPA, such as college quality and college majors. For example, the *U.S. News & World Report* Law School rankings formula assumes that one LSAT point is roughly equal to 0.084 of a point of UGPA.[83] That would appear to over-weight LSAT substantially, compared to our finding that one LSAT point is actually worth from 0.03 of a point of UGPA (for UGPA levels above 3.4) to 0.06 of a point of UGPA (for UGPA levels below 3.4).

This inflection point at 3.4 was surprising but has a plausible explanation: a

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[82] This increasing-returns UGPA model was a better fit for the data than other models we explored, including (a) a linear UGPA-LGPA relationship, (b) an increasing-returns UGPA-LGPA relationship (*e.g.*, an exponent above 1.0 on UGPA), (c) a decreasing-returns UGPA-LGPA relationship (*e.g.*, an exponent above 1.0 on UGPA), or (d) other sizes or locations for a discontinuity in the slope of the UGPA-LGPA relationship, such as placing the discontinuity at other levels from 2.7 to 3.8.

[83] Each school is ranked by *U.S. News* based on a score that is 12.5% its median LSAT score and 10% its median UGPA. *See* Sam Flanigan & Robert Morse, *Methodology: 2016 Best Law Schools Rankings*, U.S. NEWS & WORLD REPORT, http://www.usnews.com/education/best-graduate-schools/articles/law-schools-methodology (last visited Feb. 26, 2015). One additional LSAT point therefore adds 0.21% to a school's score; the quantum of additional UGPA that adds an equal 0.21% is 0.084.

higher UGPA is better, but the difference between "weak to average UGPA" (*e.g.*, 2.9 to 3.3) is less impactful than the difference between "good to great UGPA" (*e.g.*, 3.5 to 3.9)." The typical college has a roughly 3.3 mean, so 3.4 may be serving as a rough threshold for having a better-than-average UGPA.

Despite the plausibility of this finding, this sort of sudden jump in the effect of UGPA at 3.4 is probably an oversimplification, reflecting only that an inflection point was the curve of best fit for modeling what appears to be a reality that while rises in UGPA are always better, they are more significant for above-average than for weak UGPAs. Furthermore, we cannot be sure of the exact magnitude of the over-weighting – there likely are more subtle gradations from 0.03 to 0.06 than our model can estimate – but *U.S. News* likely has not run any similar study, so it's far greater LSAT-to-UGPA ratio seems to over-weight LSAT substantially as a measure of a school's student quality. A final disclaimer is that a law school with an unusually strong student body (*e.g.*, Yale, Harvard, or Stanford) or an unusually weak one (*e.g.*, schools with nearly open admissions that admit many students with UGPAs in the C grade range) might experience no such inflection point, or a different one than 3.4.

3. LCM: Modest, Decreasing Returns; 1 LCM ≈ 0.2 LSAT Pt., But with LCM<152 Amounting to an Extra -1 LSAT Point

A college's LCM, the average LSAT of its students, may be an unintuitive college quality measure. But a universal college quality metric is hard to find. Published college rankings are no viable option because they do not place all colleges on one continuum, instead ranking only the best colleges (others are listed as "unranked") and separately ranking "National Universities," "National Liberal Arts Colleges," "Regional Universities," and "Regional Colleges."[84] Similarly, rankings of colleges' research quality, even if a valid measure of college quality, do not help distinguish the quite varied quality of the many non-research-focused colleges (*e.g.*, local commuter-based public colleges).

Unlike rankings, LCM is data available for virtually all colleges that law students attended – and it does significantly predict LGPA. In the Model 1 Regression on Table 2, the coefficient for LCM is 0.003, positive and significant at the 1% level. A 1-point LCM rise is akin to a 0.215 LSAT rise, so 4.7 LCM points are akin to 1 LSAT[85] – a common difference between a flagship state school and a solid yet weaker satellite campus. But the LCM variable that best fit the data had a

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[84] *Best College Rankings and Lists*, U.S. NEWS & WORLD REP., http://colleges.usnews.rankingsandreviews.com/best-colleges/rankings?int=a8f209 (last visited Feb. 26, 2015) (separately listing four school categories and leaving several unranked in each).

[85] The coefficient on LCM, noting the effect of each LCM point, was 0.0034795; the number of LCM points necessary to equal the 0.0163022 effect of one LSAT point thus is 4.68. In addition to the relationship between LCM and LSAT, we also examined the relationship between LCM and college majors and found no evidence that college quality matters for one major versus another. Regardless of major, we found a 0.15 LGPA difference between the students in a top-quarter LCM college and students in a bottom-quarter LCM college.

discontinuity: a sub-152 LCM is akin to almost a full-point drop in an individual student's LSAT.[86] Thus, college quality matters, but (a) not as much as individual student qualities, and (b) the difference between weak and middling schools matters more than between average and strong schools.

Any discontinuity this striking could reflect quirks in the data – but we find it plausible: while college quality matters, subtle differences matter only modestly; what is most important is whether a student attended a particularly weak college – *e.g.*, those with a sub-152 LCM. Take the state of Colorado, the source of many Colorado Law students: the flagship state college, the University of Colorado at Boulder, typically has a 156 LCM (depending on the year), while the other prominent state college, Colorado State University, typically has a 153 LCM; both draw students from across and outside the state. In contrast, other public colleges in Colorado have mainly local, commuter draw: the University of Colorado campuses in Denver and Colorado Springs typically have 151 LCMs; Metro State University in Denver has a 149. The four-point discontinuity between 151 and 152 plausibly reflects that the three-point difference between the top state schools (with LCMs of 153 and 156) matters less than the difference between those two and the weaker local public colleges (with LCMs of 149-151). Admittedly, this strong a discontinuity is suspect as a literal statement; it surely is not true that all colleges with a 151 LCM are barely different from all those with a 150 yet very different from those with a 152. But an LCM-LGPA relationship with this discontinuity appears to be the curve of best fit to model a valid point: a difference between solid and strong colleges matters less than a difference between weak and solid colleges that is plausibly marked by having a sub-152 LCM.

Once we found that college quality matters, we examined whether, in addition, the predictive power of UGPA depends on college quality. Specifically, while a stronger college is better, is a higher UGPA also more of a positive predictor at a stronger rather than a weaker college? To answer this question, we ran a variant of Model 1 that estimated the difference, if any, between the effect of UGPA at (a) top-quarter LCM colleges (LCM≥158 in our sample), (b) bottom-quarter LCM colleges (LCM≤151), and (c) colleges with an LCM in the middle half (152≤LCM≤157).[87] Ultimately, we found no difference between the predictive

[86] The transformed LCM variable that best fit the data was linear, but with a discontinuity: when LCM dropped below 152, an extra four LCM points were subtracted, making the drop from 152 to 151 the equivalent of a 5-point drop. This decreasing-returns LCM model was a better fit for the data than other models we explored, including (a) a linear LCM-LGPA relationship, (b) an increasing-returns LCM-LGPA relationship (*e.g.*, an exponent above 1.0 on LCM), (c) a decreasing-returns UGPA-LGPA relationship (*e.g.*, an exponent above 1.0 on LCM), or (d) other sizes or locations for a discontinuity in the LCM-LGPA relationship, such as a smaller jump at 152, or a jump at other levels from 150 to 160.

[87] We first created dummy variables for top-quarter LCM (dQ1LCM), bottom-quarter LCM (dQ4LCM), and middle-half LCM (dQ2-3LCM). We then replaced UGPA with the following three interactive variables: (a) GPA x dQ1LCM; (b) GPA x dQ2-3LCM; and (c) GPA x dQ4LCM. This simply allowed the regression results to estimate a different coefficient for UGPA depending on whether the student's college was high-, mid-, or low-LCM.

power of UGPA at colleges with different LCMs: the coefficient on each of the three UGPA interactive terms was similar (0.157 to 0.175). Thus, college quality matters, but does not change whether UGPA matters; the difference between high and low UGPA is just as important at weaker and stronger colleges.

4. College Majors: STEM/EAF ≈ 3.5-4 LSAT Pts.; No Negative Majors

We tested seven categories of majors, with the number of observations for each group in parentheses: science, technology, engineering, or math (231); economics, finance, or accounting (160); fine arts, music, drama, or performing arts (38); environmental studies, forestry, or ecology (32); liberal arts, history, any language, or philosophy (471); psychology, sociology, anthropology, or religious studies (233); and political science, public policy, or government (428).

Among all college majors tested, only the Science, Technology, Engineering and Math (STEM) and Economics, Accounting and Finance (EAF) majors proved to have a significant effect on LGPA, and the effect was positive for both.[88] The coefficients on STEM and EAF variables, 0.066 and 0.058 respectively, were positive, similar in magnitude, and highly significant (at the 5% level). These majors were akin to having an extra 4 and 3.5 LSAT points, respectively.[89] No major predicted LGPA *negatively*: the closest was an Art, Music, or Drama major, which was a negative, but only borderline-significant (at the 10% level), and only for 1L GPA (Model 2) – and it was not at all significant as to cumulative LGPA (Model 1).

The positive STEM result was especially surprising, because we had hypothesized that while many STEM majors are more talented than their UGPAs indicate, they tend to be less experienced or inclined toward reading and writing. And we did find evidence these students may need time to grow along a "learning curve" during 1L year. Comparing the Model 1 and Model 2 results, the STEM and EAF coefficients are positive in Model 2 (1L GPA), but even more positive and significant in Model 1 (LGPA). Thus, takes time for those with STEM and EAF majors to reach their potential, but the finding remains that they outperform others.

The reason STEM majors did not suffer due to lesser reading and writing experience may be selection bias: we examined the performance of not a *random sample* of STEM majors, but the modest subset who *chose law school* – likely

[88] We coded seven categories of majors. The "Political Science/Government" major is excluded from the statistical analysis, because running regressions requires excluding one "reference group," and this group was large (428 students), and performed very close to average. We ran two OLS regressions similar to Table 2, Models 1-2, this time using liberal arts as a reference category, and the variable political science was again, positive and not significant.

[89] The coefficient on STEM, noting the effect of having a STEM major, was 0.066; the number of LSAT points (each of which has an effect of 0.0163) necessary to equal the effect of a STEM major thus is 4.09. Similarly, the coefficient on EAF, noting the effect of having an EAF major, was 0.0581; the number of LSAT points (each with an effect of 0.016) necessary to equal the effect of an EAF major thus is 3.57.

those most comfortable with reading and writing. Confirming that our STEM population was no random sample is its gender breakdown: roughly 75% of STEM majors are male,[90] yet our population's gender-STEM correlation was essentially zero.[91]

There are several possible explanations for the positive, significant effect of STEM and EAF majors. First, such majors might either train or select for technical or mathematical thinking that translates well to law study. For a major to be an LGPA predictor, not *all* those with the major must be the same; it suffices if a *higher percent* of such majors are suited to law than others are. However, undercutting the theory that STEM and EAF thinking inherently translate well to law school is the finding that STEM and EAF majors do not do as well 1L year as they do later in law school: the coefficients on STEM and EAF majors were still positive as predictors of *1L* grades, but 10-45% lower in magnitude and not as significant.[92] Thus, contrary to the view that STEM and EAF majors have cognitive styles favorable for legal study, the evidence is that such majors face some adjustment difficulty – implying that law school requires different skills, such as more written and verbal work, and more disputed interpretations than the sometimes black-and-white conclusions of science, engineering, accounting, finance, and to a lesser extent economics.

A second reason STEM (but not EAF) may be a positive predictor is that STEM courses often feature a lower grading curve, making a STEM major's 3.3 UGPA more impressive than a 3.3 in history; STEM courses typically give out fewer As and more C (or lower) grades. Thus, among students with identical UGPAs, the STEM majors show more potential – which may explain why STEM is a somewhat larger plus than EAF, in which the grading curves typically are not unusually tough.

A third reason STEM and EAF majors may be plusses is that they may have a smaller percentage of students looking for an easy ("gut") major than, say, political science or psychology.[93] This does not mean that STEM or EAF majors *actually* are harder than any others: some political science departments, and especially their top students, focus on statistical analysis as much as many economics majors do; some psychology and environmental studies majors focus on not only statistical

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[90] Kelsey Sheehy, *Colleges Work to Retain Women in STEM Majors*, U.S. NEWS & WORLD REP. (July 1, 2013), http://www.usnews.com/education/best-colleges/articles/2013/07/01/colleges-work-to-retain-women-in-stem-majors ("Only about 25 percent of STEM degree holders are women, due largely to a lack of female college students studying engineering, computer science and physical sciences such as physics and chemistry.").

[91] Specifically, the correlation coefficient between gender (male) and STEM major was 0.003.

[92] The coefficients on STEM were 0.067 for cumulative LGPA (significant at the 1% level, p=0.008) but 0.061 for 1L GPA (with far more marginal significance, only the 10% level, p=0.057). The coefficients on EAF were 0.058 for cumulative LGPA (significant at the 5% level, p=0.022) but 0.032 for 1L GPA (not significant, p=0.330).

[93] We thank Jonathan Adler for this interpretation of the predictive value of various majors.

analysis, but also biological science; and non-scientific/non-statistical academic fields like history and English are in no way inherently easier. But some fraction of college students look for easy majors because they are low on motivation, and such students may be less likely to choose to major in physics, math, or perhaps economics or finance. Even if such students are wrong in thinking courses in another field will be easier: if non-STEM/EAF majors have a higher share of low-motivation students that could explain why STEM/EAF majors eventually perform better academically.

The second and third reasons – that STEM may feature tougher grading and STEM and EAF may have a smaller share of low-motivation students – actually support a broader point than a plus factor for STEM/EAF majors: (a) extra caution may be warranted for applicants in any major with an unusually easy curriculum; and (b) extra consideration may be warranted for applicants in any major with an unusually rigorous curriculum.[94] A history or English major who took a heavy load of upper-level courses and wrote a rigorous honor thesis may be every bit as promising as a STEM major with a similar UGPA. More specifically, as noted above, many non-STEM/EAF majors do scientific or statistical work nearly indistinguishable from what STEM and EAF majors do. Yet far from all political science, psychology, and environmental studies major so focus, and it is a limitation of this study that we could not scrutinize students' transcripts to distinguish which did so; transcripts feature far too little detail in course titles to spot which courses are actually STEM/EAF-like.[95] Consequently, our results do not indicate that a mathematical, statistical, or science-focused non-STEM/EAF major is worse than a STEM/EAF major; to the contrary, the STEM/EAF plus factor seems applicable to any other major with a similarly intensive mathematical, statistical, or science focus.

One final caveat is that selecting a major is an important decision, and our findings are not prescriptive advice that aspiring lawyers should choose STEM or EAF majors. STEM, for example, may cease to be a positive predictor if liberal arts students, en masse, switched to STEM majors. Choosing a major ill-suited to one's interests or aptitude would seem a recipe for learning less, enjoying less motivation, earning lower grades, and harming the academic confidence that contributes to success. A material difference in UGPA, moreover, is a stronger predictor than any major (the 0.3 UGPA difference between B and B+ is more powerful than a STEM or EAF major), so choosing a major less suited to one's interests or talents seems a poor strategic choice, in addition to a poor educational choice.

[94] We thank Professor Jennifer Hendricks, who (despite being a math major herself) provided this point that the imprecise match between major and curricular difficulty requires a close look at the undergraduate courses applicants choose, whatever their majors.

[95] For example, the most statistics-heavy political science college courses one of the authors (Moss) took was a seminar in "American Political Institutions"; that course name on his transcript would not indicate that the course was as heavily quantitative as his economics major courses.

5. Work Duration: 4-9 Years ≈ 6.5 LSAT Points

Work duration was measured three different ways, only one of which was positive and highly significant. The coefficient for 4-9 years of work was 0.109 (positive and significant at the 1% level), akin to 6.5 extra LSAT points.[96] Working 1-3 years and working 10+ years were both positive but not significant. It was surprising that a "sweet spot" of 4-9 years' work proved better than having more *or* fewer years. We lacked a firm *ex ante* hypothesis as to the optimal quantity of work experience, the conventional wisdom in the admissions world was that work experience has roughly the sort of nonlinear relationship with LGPA that we found: while work experience is a plus, and more is better, too much is a negative. To test whether increasing years of work experience had this sort of initially increasing, but then decreasing, effect on LGPA, we ran a correlation matrix of LGPA and each number of years of work experience (1, 2, 3, etc.). The correlations showed a fairly clear break between 1-3 years, 4-9 years, and 10+ years: 4 years through 9 years each showed a fairly consistent positive correlation with LGPA; yet there was no clear relationship (positive or negative) for 1-3 years or for 10 or more years.

We offer a two-part likely explanation for 4-9 years' work experience being an apparent sweet spot for law students. First, the difference between 1-3 and 4+ years likely reflects a maturity difference. Having work experience (compared to starting law school right after college) either provides or selects for maturity, but 1-3 years may not truly provide real-world experience. Someone in law school after only one year of work was applying to law school that entire year; with 2-3 years of work, the student still was applying or studying for the LSAT halfway through those years, and probably planning to apply to law school from the start. Thus, 1-3 years of work is not enough to provide the experience of making one's way in the world before law school; that length serves only as a waystation between college and law school.

Second, the difference between up to 9 years and 10+ years likely reflects the difficulty some longtime workers have readjusting to school. Those with 10+ years include many with the best experience and maturity, but also many with trouble readjusting to student life, which could explain why having that much work is, on average, neither a positive nor a negative; it includes a mix of plusses and minuses.

To be sure, as with other nonlinear relationships we found, the bright lines in our work experience dummy variables should not be relied upon too literally: some people mature greatly with 2-3 years' work, while others do not mature with 4-5; some with 7-8 years have trouble readjusting while some with 12-13 readjust easily. The idea of a 4-9 year sweet spot is thus an oversimplification, but one that we think reflects a reality, and one that comports with some conventional wisdom in the law admissions world: work experience is a material plus factor, a proxy

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[96] The coefficient on having 4-9 years' work was 0.109; the number of LSAT points (each with an effect of 0.0163) necessary to equal the effect of 4-9 years' work thus is 6.66.

either for maturity or for having made an informed decision to take the plunge back into student life; but just a few years of work is too little to make a difference, and too many years risks making it difficult to readjust back to student life.

6. Work Type: Teaching ≈ 5 LSAT Pts.; Military ≈ -7$^1/_3$; Sci/Tech ≈ -3

Of the six categories of employment, two proved significant LGPA predictors: teaching experience had a coefficient of 0.082, positive and significant only at the 10% level; military experience had a coefficient of -0.119, negative and significant at the 5% level. Science and technology experience had a coefficient of -0.077, but was significant only at the 10% level, and only in Model 2, the 1L GPA regression. No other category was significant.

Teaching experience is akin to 5 extra LSAT points,[97] which likely reflects personal qualities. Among jobs held in the early- to mid-twenties age of most entering law students, teaching may be the one that most selects for – or develops – the ability to be a responsible adult wielding authority and urging others to take work seriously. Also, choosing a teaching career in one's early twenties likely indicates comfort in a learning environment, which bodes well for meeting the demands of law school. Thus, while teaching work may confer some benefit, more likely it is that having selected a teaching job reveals a student to be of a type – responsible and comfortable with classroom learning – likely to do well in law school.

Military experience is akin to -7$^1/_3$ LSAT points.[98] However, most law students from the military had several years of service, placing them in the 4-9 years' work category that is a countervailing plus of similar magnitude. The plus of lengthy work and the minus of military work therefore roughly cancel out; *i.e.*, 4-9 years in the military is not materially better or worse than having no work experience at all.

The reason military work is essentially the opposite of teaching as a predictor is likely because they select for different traits and backgrounds. As noted above, those choosing teaching may adjust to three years of classroom lectures and textbook reading easily. In contrast, more of those choosing the military may find law school a difficult adjustment for two reasons. First, whereas teaching selects for those comfortable with classroom learning, the military may select for kinesthetic learners, providing learn-by-doing experience that makes the more passive experience of law school a major adjustment. Second, military experience may be a negative predictor as a proxy for low socioeconomic status. Pentagon data show that the military "lean[s] heavily for recruits on economically depressed, rural areas … , with nearly half coming from lower-middle-class to poor households."[99] Those from less privileged socioeconomic backgrounds not only

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[97] The coefficient on teaching experience was 0.082; the number of LSAT points (each with an effect of 0.016) necessary to equal the effect of 4-9 years' work thus is 5.02.

[98] The coefficient on military experience was -0.119; the number of LSAT points (each with an effect of 0.016) necessary to equal the effect of military experience thus is -7.32.

[99] Ann Scott Tyson, *Youths in Rural U.S. Are Drawn To Military*, WASH. POST (Nov. 4, 2005),

may face a tougher adjustment to the culture and expectations of law school,[100] but – especially following recent decades of rising tuition – are more likely to need to divert time to paid work during law school, further negatively impacting their grades.[101]

Comparison of the 1L and cumulative LGPA results corroborates the adjustment-difficulty theory of why military work predicts negatively. Military work predicts a 0.118 lower cumulative LGPA, but a 0.231 lower 1L GPA; thus, the effect on 1L LGPA is nearly double the effect on cumulative LGPA. Similarly, scientific or technical work experience – which also might make for a difficult adjustment to law school – is not a significant predictor of cumulative LGPA (it is akin to -3 LSAT, but the correlation is not statistically significant[102]), yet is a mildly significant negative predictor of 1L GPA. This corroborates that some jobs may be negative predictors because they are so different from law study that law school requires a major adjustment that many can make eventually (as shown by the cumulative GPAs being better than the 1L GPAs), but many do not make (as shown by the continued negative effect of military work after 1L year).

7. Negative Criminal/Disciplinary Record ≈ -7$^{1}/_{3}$ LSAT Points

The coefficient on the variable for having a significant negative or criminal record was -0.119, negative and significant at the 5% level; it was also negative and significant in this magnitude in the 1L GPA regression. A negative record thus

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http://www.washingtonpost.com/wp-dyn/content/article/2005/11/03/AR2005110302528.html ("[T]he military is leaning heavily for recruits on economically depressed, rural areas where youths' need for jobs may outweigh the risks of going to war. … Many of today's recruits are financially strapped, with nearly half coming from lower-middle-class to poor households, according to new Pentagon data … . Nearly two-thirds of [2004] Army recruits … came from counties in which … income is below the U.S. median").

[100] Eli Wald et al., *Looking Beyond Gender: Women's Experiences at Law School*, 48 TULSA L. REV. 27, 45-49 (2012) (describing, from first-hand student account, how and why low-socioeconomic status background led to poor grades and overall performance in law school).

[101] Eli Wald, *The Visibility of Socioeconomic Status and Class-Based Affirmative Action: A Reply to Professor Sander*, 88 DENV. U. L. REV. 861, 866-67 (2011) (noting that law school, especially the first year, "involves reading significant volumes of case law. Sixty-, seventy-, and even eighty-hour weeks are not unheard of, and a part-time or full-time job may put one at a significant disadvantage," and thus, "the possible need of some students of lower socioeconomic status to work either part-time or full-time while enrolled … may also constitute a significant hurdle to one's academic success"). *Cf.* NALP FOUNDATION FOR LAW CAREER RESEARCH AND EDUCATION (NALP) AND AMERICAN BAR FOUNDATION (ABF), AFTER THE JD: FIRST RESULTS OF A NATIONAL STUDY OF LEGAL CAREERS (2004) (corroborating Wald's hypothesis that students from lower incomes have more need to work, by reporting that students from more affluent backgrounds graduate with less debt: "Individuals with no educational debt leaving law school were more likely … to be white or Asian, and of higher socioeconomic status.").

[102] The coefficient on scientific or technical experience was -0.0504446; the number of LSAT points (each with an effect of 0.0163022) necessary to equal the effect of scientific or technical experience thus is -3.09. But the coefficient was not statistically significant (p=0.121).

appears to be is a significant negative, akin to almost -7$^{1}/_{3}$ LSAT points.[103]

This finding was somewhat surprising because the pool of law students with negative records is a biased subsample of the population with such records. Law schools reject those with the worst records, or those with the weakest explanations of their records. Yet even this positive-biased sample of those with records performed worse on average. Likely, the population with negative records is a heterogeneous mix of some who are fine and some who lack necessary personal qualities (discipline, self-control, drive, etc.) to succeed.

A notable caveat to this finding is that although most variables in this study were objective numbers or binary conditions, two were highly subjective: deciding what was a significant criminal or disciplinary record; and deciding what was a major leadership role. A great many students have a modest negative record (particularly common are drinking alcohol underage or marijuana possession), just as a great many have some modest leadership experience (*e.g.*, being an officer in a small college club). Thus, we noted only major negative records or major leadership roles, to avoid lumping into one yes-or-no binary variable all negative records from public drinking to major felonies, or all leadership roles from president of a bridge club to president of a student government. This need to impose a threshold added subjectivity, however. We tried to limit that subjectivity by giving guidance and on-site supervision to those entering data: (a) that "major criminal or disciplinary record" means anything more than merely using a controlled substance underage, or privately without any violence or selling of the controlled substance; (b) that "major leadership role" means a high officer position in a major organization (*e.g.*, Treasurer of an entire college student government) or being the top leader of multiple smaller organizations (*e.g.*, president or captain of a bridge club and a mock trial team); and (c) that one of the authors was in the room for all data entry and should be consulted about any borderline cases -- to maximize the extent to which the threshold of "major" was applied consistently, even if with unavoidable subjectivity

8. Rising UGPA (If in Law School Right after College) ≈ 2 LSAT Points

The coefficient on a rising undergraduate UGPA was 0.053, positive and significant at the 10% level in the 1L GPA regression only. This supports the calculation that a UGPA rising by at least 0.3 by the end of college was a positive predictor, akin to 2 LSAT points,[104] but with two caveats. First, rising UGPA did not correlate with LGPA for those with work experience.[105] Second, rising UGPA

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[103] The coefficient on negative criminal or disciplinary record was -0.1190152; the number of LSAT points (each with an effect of 0.0163022) necessary to equal the effect of scientific or technical experience thus is -7.30.

[104] The coefficient on having a rising UGPA, for those right out of college, was 0.032; the number of LSAT points (each with an effect of 0.016) necessary to equal that effect thus is 2.01. But, as noted below, the coefficient was not statistically significant (p=0.146).

[105] More precisely, the dummy variable was the product of two other dummy variables: rising UGPA (1=yes, 0=no) multiplies by no work experience (1=yes, 0=no). This result makes sense:

was not a statistically significant predictor of cumulative LGPA.[106] Like LSAT, a rising UGPA predicts a higher 1L GPA more strongly than it predicted a higher cumulative LGPA. Thus, having a rising GPA may be a plus, but an ephemeral one, reflecting that those who did well late in college, then attended law school right after, are performing above par to an extent not likely to persist.

9. Demographics: Person of Color Self-ID, -9 to -9½ LSAT Pts.

Any self-identification as a person of color – African-American, Latino/a, Asian-American, or Native American – was a statistically significant negative predictor of both LGPA and 1L GPA. The coefficients for African American, Latino/a, Asian American and Native American categories were -0.155, -0.148, -0.154, -0.173 respectively; all but Native American are significant at the 1% level, and Native American is significant at the 5% level. However, even with a combined dataset from two schools, the number of observations in the categories – African American (59), Latino/a (45), Asian-American (142), and Native American (15) – is relatively low.[107] A group of 15 is too small from which to draw conclusions, and even 45 is relatively low.

Still, the magnitude of the racial disparity was substantial and relatively consistent: each category of person of color self-identification was akin to -9 to -9½ LSAT points.[108] In contrast, gender had no effect. This racial disparity is our most challenging to interpret: we have only modest space to devote to each of our many findings, yet racial disparity is an extraordinarily complex social phenomenon. A full analysis of racial disparities – including relevant sub-issues such as bias, affirmative action, alienation, stereotype threat, etc. – is far beyond the scope of this paper; whole articles or books exist to analyze such topics. Still, our findings hint that some explanations have more persuasive power than others.

Our finding provides evidence that racial disparities in law school performance cannot be entirely the result of members of racial minorities being "mismatched" to their schools due to affirmative action helping them gain admission with lesser

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UGPA trajectory is recent information for those starting law school right after college, but not for those whose college work was years ago. Thus, the only rising UGPA trait that correlated with LGPA was an interactive term of those who had a rising GPA and were attending law school right after college.

[106] The coefficient was 0.034 with a p-value (0.126) near but not reaching the 10% level marking modest significance.

[107] *See* Appendix, Table 4 (listing all variables and summary statistics).

[108] The coefficients on African-American, Latino/a, Asian-American, and Native American were -0.155, -0.148, -0.154, and -0.172, respectively; the number of LSAT points (each with an effect of 0.016) necessary to equal those effects thus are -9.53, -9.09, -9.47, and -10.61, respectively. However, we do not place much weight on the coefficient for being Native American because, as noted above, the sample size of that group was too low to allow any valid conclusions, leaving us reporting mainly the other groups that predicted as akin to -9 to -9.5 LSAT points.

credentials, as Richard Sander hypothesized.[109] We find racial disparities despite controlling, better than prior studies do, for not only academic ability on standardized tests (*i.e.*, LSAT) and prior academic performance (*i.e.*, UGPA), but also a number of other variables relevant to academic credentials, such as college quality, college major, and UGPA trajectory (all factors helping distinguish between the predictive power of similar UGPAs), as well as various nonlinear relationships LGPA has with college quality and UGPA.[110]

To more closely examine whether a correlation between race and entering credentials could explain the disparity, we re-ran the Model 1 regressions on two subsets of the data: (a) just those with a bottom-quarter "index" (i.e., a linear combination of LSAT and UGPA into one number); and (b) those with an LSAT-UGPA in the first to third quarter. We found that, among African-Americans (but not other people of color), having an index not in the bottom quarter more than halved the disparity: the predicted LGPA impact was -0.207 for those with a bottom-quarter index, but -0.093 for others. Thus, controlling as carefully as possible for academic credentials lessens the disparity, but does not eliminate it.

Given that controlling as much as possible for low entering academic credentials lessens the disparity only for African-Americans, and only by about half, it seems likely that the racial disparity reflects something not merely about the students, but about legal education itself – which may be unsurprising, given the substantial literature on how people of color, and those with less privileged socioeconomic backgrounds, can find law school alienating or a challenging adjustment, to the detriment of their performance.[111] A full survey of the literature on alienation, stereotype threat, and other similar phenomena is beyond the scope of this paper – but such phenomena are well-documented and long-known. Lani Guinier noted two decades ago, from survey and academic performance data, that women, then a minority of law students, found law school a source of "alienat[ion]" and "distress" – and performed worse in law school despite credentials on par with those of men:

> [W]e find strong academic differences between graduating men and women. Despite identical entry-level credentials, this performance differential … is created in the first year of law school and maintained

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[109] Richard H. Sander, *A Systemic Analysis of Affirmative Action in American Law Schools*, 57 STAN. L. REV. 367, 453-54 (2004) (arguing as to law school admission, and reviewing prior literature so arguing as to undergraduate admission, that due to "large racial preferences," African-Americans often "go[] to a school where one's academic credentials are well below average[, which] has powerful effects on performance. … [S]uch a student is learning less than she would have learned at a school where her credentials were closer to average.").

[110] As with our other variables, we do not believe there is anything unique about the two schools we studied. The racial disparity was significant at both, even though each features a national, but relatively different, geographic population; each draws the majority of its students from outside its own state, and both have many east coasters, but Colorado draws more heavily from the west and Texas, while Case Western draws more from the Midwest and parts of the South.

[111] *See supra* Part IV(B)(9).

> over the next three years. By the end of their first year … , men are three times more likely than women to be in the top 10% of their law school class.[112]

If anything, it is surprising that we found only racial disparities, not the gender disparities Guinier documented. Our findings thus evidence progress in eliminating law school gender disparities, but not racial disparities – warranting further support for struggling or alienated students, as we later discuss.[113]

Unconscious bias is another possible explanation for the racial disparity. We do not assume, and know no evidence of, systemic bias by many or most law professors. Implicit bias has been shown to be pervasive in human cognition,[114] however, so it is always a possible explanation worth exploring for any racial disparities. While most law school examinations are graded anonymously, bias still can infect (a) the non-anonymous class participation plus-minus factors that can make course grades differ from exam grades, and (b) the many classes are not anonymously graded, such as seminars, clinics, and most skills courses. Because of the modest size of the racial disparities we found – averaging about 0.15 in LGPA – even episodic, limited bias could be enough to explain a material portion of the disparities.

C. *The Quarter Regressions (Models 3 and 4): What Predicts Especially Strong or Weak Law School Performance?*

Models 3 and 4 attempt to predict who lands in the top quarter ("Q1") or bottom quarter ("Q4") of their law school classes. Since presence in a quarter is a dichotomous variable, Models 3 and 4 use logistic regression to predict the odds each student will be in the top or bottom quarter.[115] Table 7 in the Appendix reports the findings of the Quarter Regressions as odds ratios.[116] Odds ratios are used to compare the relative odds of the occurrence of a particular outcome. The

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[112] Lani Guinier et al., *Becoming Gentlemen: Women's Experiences at One Ivy League Law School*, 143 U. PENN. L. REV. 1, 2-3 (1994) (finding the female minority at the University of Pennsylvania Law School experienced "alienat[ion]" and "distress," based on academic performance data from 981 students and self-reported survey data from 366 students).

[113] *See infra* Part V (noting possible prescriptions for admissions reform).

[114] Anthony G. Greenwald & Linda Hamilton Krieger, *Implicit Bias: Scientific Foundations,* 94 CAL. L. REV. 945, 955-56 (2006) (reporting various findings, such as that only 20% of survey respondents displayed "explicit" bias but 64% displayed "implicit bias," and concluding that the data "strongly suggest that any non-African American subgroup … will reveal high proportions of persons showing statistically noticeable implicit race bias" against African-Americans).

[115] Specifically, on the full data set, we regressed dichotomous dependent variables Q1 and Q4 (top- and bottom-quarter LGPA) on all independent variables; each independent variables' coefficient thus estimates its effect on the logarithm of the odds of the dependent variable (*i.e.*, presence in the quarter), adjusting for all other variables included in the model. In Stata, the logistic command produces results in terms of odds ratios while logit produces results in terms of coefficients scales in log odds.

[116] Logistic results can be interpreted in one of two ways. A variable's coefficient is the "log odds of the dependent variable," or the exponentiated coefficient is the "odds ratio."

results can be interpreted as in the following example from the Table 7 (Q1) regression: the odds ratio for having 4-9 years of work experience is 2.78, so the odds of this student being in the top quarter are 178% greater when the student has this work experience; in contrast, the odds ratio for having 10+ years' work experience is 0.69, meaning that the likelihood of this student being in the top quarter decreases 31%, or 1-0.69. The odds ratios indicate the increased likelihood (or decreased likelihood in the case of values under 1.00) of a certain effect; an odds ratio of (or close to) 1.00 indicates no effect.

Most results were similar to the Model 1 LGPA results, as expected: if a factor predicts law grades generally (Model 1), it also predicts whose grades are the best (Model 3) or worst (Model 4). We lacked strong *ex ante* hypotheses as to what predictors would differ from Model 1 to Models 3-4. We nevertheless thought it important to examine whether any factors, apart from predicting grades generally in Model 1, further predict who becomes (a) a Q1 high achiever likely to land top jobs (*e.g.*, clerkships, large firms, or elite public interest jobs), or (b) a Q4 low achiever less likely to land quality jobs or pass a bar exam.[117]

What is notable about Models 3-4 is where they either (a) found significant predictive power in variables that were not significant in Model 1, or (b) helped pinpoint whether a significant predictor in Model 1 (*e.g.*, STEM) more strongly predicted high success odds (*i.e.*, Q1) or low odds of failure (*i.e.*, Q4).

- **Higher Odds of Q4, But Not Lower Odds of Q1: Military and Science/Technology Work**. We expected military work, a negative Model 1 LGPA predictor, to predict being in the top or bottom quarter of the class in terms of LGPA. Students with military work experience are 209% more likely to be in the bottom quarter of the class (Q4). We did not expect science/technology work (not a significant Model 1 LGPA predictor) to be positive and significant in the quarter regressions. Yet students with science/technology work experience are 83% more likely to be in Q4. This supports the view that the reason military work, and to an extent science/technology work, predicts negatively is not that most have lower aptitude, but that some fraction have difficulty adjusting – which is why the impact is higher odds of Q4, not lower odds of Q1.

- **Higher Odds of Q1: STEM, and EAF to lesser extent.** Both majors are similar-sized positive predictors of LGPA, yet STEM has a much larger effect in predicting higher Q1 odds. STEM majors are 71% more likely to be the Q1 compared to EAF majors who are 30% more likely to be in the Q1. This partially supports the "hard curve" theory

[117] LINDA F. WIGHTMAN, LAW SCHOOL ADMISSIONS COUNCIL, INC., LSAC NATIONAL LONGITUDINAL BAR PASSAGE STUDY 23-24 (1998), http://www.unc.edu/edp/pdf/NLBPS.pdf (concluding from empirical study that LGPA and LSAT were the two most significant predictors of the odds of passing a bar examination, and in particular that LGPA correlated more strongly than LSAT did with bar outcome).

of why STEM predicts well: both STEM and EAF majors arguably contain fewer weak students, but perhaps STEM has the tougher grading curve, which may be why STEM majors have the higher likelihood of being in the Q1.

- **STEM Predicts Q1 While Sci/Tech Work Predicts Q4**. There is some inconsistency between STEM majors predicting higher Q1 odds and science/technology work (which correlates with having a STEM major) predicting higher Q4 odds. This supports the theory that certain groups, like scientists, are high-variance populations: some are high performers whose talents outstrip their LSAT/UGPA predictors; others are low performers who never adjust to the differences between science and law.
- **Graduate Degrees and Rising GPA Predicts Lower Odds of Q4**. This relationship is similar for rising UGPA and graduate degrees (both significant at the 10% level), but this is the only notable finding as to graduate degrees. A graduate degree makes a student 32% less likely to be in the Q4; a rising UGPA makes one 34% less likely to be in the Q4. This hints that the import of rising UGPA is not that it shows greater intellect, *i.e.*, not that the student who rose from 3.3 to 3.7 is smarter than the one with a consistent 3.5. Rather, rising UGPA shows a student learned to succeed academically; it may be on the same logic that completing another graduate program indicates lower odds a student will fail to perform in law school.
- **Lower Odds of Q4: Male and Asian-American Students**. These results were contrary to the Model 1: while male students do not do better overall (Model 1), they are 28% less likely to be in the Q4; and while all nonwhite ethnicities do worse overall (Model 1), Asian-Americans are 62% less likely to be in the Q4. The gender finding may be evidence that while long-noted gender disparities have abated, they are not fully gone; *e.g.*, perhaps some professors are more likely to "save" a weaker student from a low grade if he is male. The inconsistent ethnicity findings, though, may be a mere statistical quirk, given that the low sample sizes for these groups becomes even lower when only a quarter of the dataset is in the regression (as in Models 3 and 4).

D. The "Splitters" Regression (Model 5): Which Is Better, High-UGPA/Low-LSAT or the Reverse?

Because LSAT and UGPA both are powerful predictors of LGPA, a tradeoff of one versus another, theoretically, could be a wash. [118] But law schools do not

[118] The tradeoff between LSAT and UGPA with respect to first year law 1L GPA has been studied extensively by LSAC, who find in their studies a correlation coefficient between LSAT and first year law GPA to be 0.36 and between UGPA and first year law GPA to be 0.27. *See*

behave as if that were the case; high-LSAT/low-UGPA candidates are far more likely to win admission and scholarship offers than low-LSAT/high-UGPA candidates, as documented above.[119] Model 5 thus explores whether this strong law school preference for high-LSAT over high-UGPA students is (a) a valid preference reflecting the superiority of the former, or (b) a preference that is misguided and/or a mere effort to boost the LSAT median that *U.S. News* over-weights.

Like Model 1, Model 5 aims to predict LGPA from all independent variables, adding two "splitter" profiles: high-LSAT/low-UGPA and high UGPA/low-LSAT. The "mild splitters" regression examines students from both schools who had a top-50% LSAT but bottom-50% UGPA and vice-versa.[120] The model includes a dummy variable for students who fit the high-LSAT/low-UGPA profile, a shortened list of predictor variables[121], and an "index" variable combining LSAT and UGPA, used to control for whether the splitter type has a higher LSAT-and-UGPA average.[122]

The key finding is that in predicting LGPA, high-LSAT and high-UGPA splitter profiles are not equal. *High-LSAT*/low-UGPA splitters perform subpar, controlling for all other variables, including the LSAT-UGPA index. The coefficient for the high-LSAT splitters was -0.052, negative and significant at the 5% level. This means that high-LSAT/low-UGPA profile predicts lower LGPA, compared to high-UGPA/low-LSAT splitters. Appendix Table 8 presents the

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Anthony, Lisa A. et al., *supra* note 70. Our findings are identical to those in the 2013 LSAC study, showing LSAT to be the stronger predictor of 1L GPA. We find that over time, the LSAT loses its relative strength over UGPA as a predictor of LGPA. In our study, the correlations between LSAT and LGPA, and UGPA and LGPA were 0.28 and 0.29, respectively -- nearly the same.

[119] *Supra* Part III(B)(2)(c).

[120] The 'mild splitters' subset contains 733 students from both schools: 396 students had a top-50% LSAT but bottom-50% UGPA, and 337 students had a top-50% UGPA but bottom-50% LSAT. In the regression, a dummy variable was used for the top-50% LSAT but bottom-50% UGPA profile (coded "1"). For robustness, we also ran an "extreme splitters" regression which contained 192 students from both schools: 142 students had a top-25% LSAT but bottom-25% GPA, and 80 students had a top-25% UGPA but bottom-25% LSAT. Again, a dummy variable was used for the high-LSAT/low-UGPA profile. The low number of observations of extreme splitters were too few to test many variables; nonetheless, we ran this OLS regression and did not find any significance indicating a preference toward any extreme splitter category.

[121] This regression with 733 variables does not include these predictors with fewer than 40 observations: African American, Latin American, Native American, 10+ years of work experience, military work history, Art major, environmental sciences major.

[122] The index variable equals LSAT+ (UGPA*10). We used the index in the splitter regressions (instead of UGPA and LSAT) because the index was not highly correlated with the splitter variable. The correlation between LSAT and the splitter variable was mildly high (r=0.40); the correlation between UGPA and the splitter variable was very high (r=-0.73); the correlation between the index and the splitter variable was low (r=-0.04).

Model 5 OLS regression testing for the significance of the high-LSAT/low-UGPA profile. Using 733 observations -- containing mild splitters (of both types) – this regression tested the significance of the dummy variable for the high-LSAT/low-UGPA profile.

If high-LSAT/low-UGPA splitters perform subpar compared to high-UGPA/low-LSAT splitters using a subset of only mild splitters (733 observations), a follow-up question to ask is how do high-UGPA/low-LSAT splitters perform compared to non-splitters (1435 observations) as a whole? For robustness, we ran a second OLS regression this time including all variables, the index in place of LSAT and UGPA, and a dummy variable for the high-UGPA/low-LSAT splitters group. The coefficient on the high-UGPA/low-LSAT splitter was 0.23, positive and not significant, indicating that the *high-UGPA*/low-LSAT splitters did no worse or better than non-splitters. To conserve space, we report these results here and do not present them in a table format.

One caveat to this finding is that a high-LSAT/low-UGPA profile *may* still be equal or superior to other profiles, because the result may trace to selection bias discussed earlier in Section IV. As noted above, schools admit the vast majority of high-LSAT/low-UGPA candidates, but a minority of low-LSAT/high-UGPA candidates. By so liberally admitting high-LSAT splitters, schools may be admitting some who are less likely to succeed – whereas by hand-picking among high-UGPA splitters, schools are choosing more solid students. If schools admitted high-UGPA splitters as liberally as they admit high-LSAT splitters, then the former might suffer the lower average LGPA we see from the more indiscriminately admitted high-LSAT splitters.

Even with this caveat, two notable findings remain. First, high-UGPA/low-LSAT splitters, when chosen as carefully as is current practice, are no less promising than those with a more balanced profile or a higher LSAT, so schools need not fear dipping too low in LSAT for a candidate with a high UGPA or other plusses. Second, the worse performance of high-LSAT/low-UGPA splitters indicates that schools may too indiscriminately admit those with a high LSAT but few other plusses.

E. The Variance Analysis: Examining LGPA Variance Based on Membership in Various Groups

Finally, we examine the absolute variance of LGPA for each group defined by a binary dummy variable, *e.g.*, each group of majors, jobs, and splitters, and also relative variances. Variances are reported on Table 9. If group X has higher variance than group Y, then group X is a more heterogeneous mix of high and low performers. That would indicate that group X is a high-risk/high-reward mix warranting more individualized scrutiny of its members – both to try to spot the extreme high-performers to admit eagerly, and the extreme low-performers to avoid. Comparison of LGPA variance is most meaningful among groups of similar sizes, because variance tends to decrease as sample size increases, so the following are summaries of which groups have higher LGPA variance than others of similar sizes.

- **Military Experience.** This was the one work group that was a negative predictor, but the high variance (0.0046, compared to 0.0005-0.0029 for other groups of similar size) shows it includes a wide mix of high and low performers. This adds nuance to interpreting the negative coefficient: the group does not predict uniformly negatively; it sees more bad than good outcomes, but so much variance that good outcomes remain for a subset.
- **Criminal/Disciplinary Record.** This was the most negative predictor, but its high variance (0.0018, compared to 0.0007-0.0013 for other groups of similar size) supports interpreting this group, too, as a heterogeneous mix. As with military experience: given a significant negative coefficient *and* high variance on a binary dummy variable, the effect is not that *all* with a negative record perform worse; rather, it is that some fraction do *much* worse.
- **Public Sector Experience.** This group also had high variance (0.0017, compared to 0.0007-0.0013 for other groups of similar size, and higher than all other work categories),[123] corroborating a "gunners and meanderers" interpretation: those with traditional pre-law backgrounds do average overall, but feature a mix of (a) a few very high-performing "gunners" unusually motivated to be lawyers, and (b) many "meanderers" with weak motivation who attended law school as a path of least resistance for those with their majors and work experience. On this view, those with traditional law backgrounds perform average overall, but are a heterogeneous mix of high- and low-motivation students deserving careful scrutiny.

Overall, the above high-variance groups (high relative to other groups similarly sized) mark populations that may or may not successfully adjust to law school: those with (a) military experience that may be especially different from law study, (b) criminal/disciplinary records that may or may not hint at serious problems, or (c) traditional pre-law backgrounds that include a mix of high motivation for law study and low-motivation students who applied as a path of least resistance. The heterogeneity of applicants from high-variance groups means that, rather than paint with a broad brush in predicting their success or failure, schools should carefully scrutinize such applicants for other indications that they are more likely or less likely to succeed in law school, *e.g.*: a personal statement or resume items making a persuasive case for high motivation for law study; for splitters, high or low writing quality, or unusually strong academic recommendations, could break the tie between dueling academic predictors such as a high UGPA and a low LSAT (or vice-versa).

[123] LGPA variance was fairly consistently at or near 0.0010 for all other work categories: business (0.0010); teaching (0.0013); science, technology, or medicine (0.0009); and legal (0.0009).

Finally, and in contrast, following are groups that we hypothesized might be high-variance mixes of high and low achievers – but that ultimately did *not* feature higher LGPA variance than other similarly sized subsamples.

- **Splitters.** We hypothesized that high-LSAT splitters are risky holders of unfulfilled potential, or that *both* splitter types might show high variance, because an LSAT-UGPA gap hints at a wide range of outcomes. But both splitter types had LGPA variances on par with other similar-sized groups (work types, majors, etc.): the splitters' variances were 0.0007-0.0011, compared to 0.0009-0.0013 for other groups. Thus, there is no reason to be more skeptical of a splitter than a candidate with more UGPA-LSAT balance; a higher UGPA balances a low LSAT, and vice-versa, without any penalty or extra unpredictability for an unbalanced splitter profile.
- **Longer Work Experience.** We hypothesized that those with especially long work experience, even if not worse overall, are a riskier mix of mature second-career aspirants and those who might find it too difficult to re-enter academia. But those with 4-9 years or 10+ years of work experience had no greater variance than other similar-sized subgroups (work types, majors, etc.). Accordingly, there is no evidence supporting extra skepticism of those long removed from college due to lengthy work experience.

F. Notable Non-Findings: Variables with Little or No Relationship to LGPA, Contrary to Our Hypotheses or Common Assumptions

Earlier sections detailed all findings as to all variables that proved significant predictors, positive or negative, of LGPA. This subpart, in contrast, details variables that did *not* prove significant LGPA predictors. We report these non-findings for the same reason tested these variables in the first place: we had hypothesized, and/or prevailing admissions practices have assumed, that they might help predict LGPA.

1. Nontraditional Pre-Law Majors: Not a Negative

One hypothesis was a negative effect on LGPA of various nontraditional pre-law majors: performing arts (*e.g.*, art, music, and drama); environmental studies (which included related, more specific majors, such as forestry); and STEM majors. These three groups cover all majors other than the more traditional pre-law majors: political science, any other social sciences, and any liberal arts subjects. STEM was a subject of dueling hypotheses – perhaps they are elite majors, or perhaps they are too foreign to law study – and the findings in Table 2, Models 1-2, show that the coefficient for STEM is 0.061, positive and significant at the 10% level for 1L GPA, and 0.066, positive and significant at the 5% level, for LGPA. It is slightly larger and more significant coefficient in the LGPA regression presumably because STEM majors need time to adjust. The other two groups of nontraditional pre-law majors – performing arts and environmental studies – were hypothesized to be negative predictors.

Yet neither arts- nor environment-related majors had any significant relationship with LGPA. Either students with such majors are just as prepared as others for law study, or there is a selection bias: relatively few such majors attend law school (there were 70 arts-related and environmental-subject majors, roughly 5% of the sample), so perhaps the few performing arts or environmental majors who choose law school are those with more preparation or aptitude for legal study. Whatever the explanation, there appears to be no basis for extra skepticism for nontraditional pre-law majors – though difficulty of curriculum may remain relevant, because it may be one explanation of why STEM majors perform above-par.

2. Traditional Pre-Law and Reading-Heavy Majors: Not a Positive

Law school classes are reading-intensive, and most grading is of prose essay- and paper-writing, so we hypothesized that LGPA would positively correlate with majors that do more reading and writing, such as political science, liberal arts (*e.g.*, history or English), or social sciences (*e.g.*, psychology, sociology, or anthropology). Yet no such majors correlated significantly with LGPA.[124]

Modest support for the reading-as-preparation hypothesis did, however, appear in how some variables more negatively predict 1L than cumulative LGPA: military or technical work; and STEM or EAF major. That such students needed time to reach their potential hints that the *absence* of recent reading or writing experience (*e.g.*, working in technical or military jobs less likely to entail reading and writing) is more important than subtle differences among majors in reading and writing content.

3. Traditional Pre-Law Work (Legal and Public Sector): Not a Positive

We hypothesized, and it is a common assumption in law admissions, that the sort of quasi-legal work available before law school (paralegal, caseworker, etc.) is a positive predictor of law school success, for various reasons: it could provide training in legal study that gives a leg up, at least during 1L year; it could be a proxy for high motivation to be a lawyer; or it could provide exposure to the unglamorous side of legal work, making those who still forge ahead with law school less likely to get disillusioned later (*e.g.*, a former paralegal is not going to be shocked that law study is more about paperwork than about being a spellbinding courtroom orator).

Legal work was not a significant predictor of LGPA in any model. This undercuts the above hypotheses; perhaps it also indicates that, thanks to bans on

[124] The Political Science/Government major is the reference category and dropped in the Model 1 regression. If we re-run Model 1 and intentionally drop a different major (environmental science), the Political Science/Government major has positive coefficient but it is far from significant, therefore it does not demonstrate a statistical and reportable relationship with LGPA.

unauthorized practice of law, legal work before law school is likely low in responsibility and substance, and thus a less impressive experience, than many teaching, engineering, computer programming, or other jobs.

4. Prior Graduate Degrees: Not a Positive

The one modest predictive effect of a prior graduate degree is lower odds of a Q4 LGPA – but this was a modest effect (significant at only the 10% level), and overall, prior graduate degree had no overall correlation with LGPA. We were surprised prior graduate degrees were not predictors of LGPA, as markers of either higher academic ability, success at graduate-level work, or passion for academics.

There are three possible reasons for this lack of a provable relationship between prior graduate work and LGPA. First, the vast majority of other graduate degrees held by law students are master's degrees, so our finding is mainly that master's-level work is non-predictive; PhDs may well be predictive but are too rare for a useful sample size, even in a two-school, four-year sample.

Second, master's degrees are quite heterogeneous; perhaps an M.B.A., an engineering master's, a teaching master's, and a social work master's predict differently. But, again, the sample sizes were not high enough to divide master's degrees into multiple categories.

Third, even if a subset of graduate degrees may be a plus, that subset may correlate with other positive variables. For example, scientific graduate degrees may be a positive, but those with such degrees typically had STEM majors as well, which itself is a positive significant predictor.

In sum, it remains possible that a subset of graduate degrees may be a positive, but graduate degrees are too heterogeneous to so prove. Still, our findings undercut any conventional wisdom that simply having a master's degree is a plus by itself.

5. Major Leadership Roles in College: Not a Positive

The leadership roles students often pursue, and view as resume-builders, were not a significant predictor of LGPA. This finding comes with two major caveats. First, the definition of a "major" leadership role is subjective. That subjectivity was unavoidable and, as discussed in Part IV(B)(7) above (the section on the similarly subjective variable for major criminal/disciplinary record) was mitigated by various efforts to define the term and provide consistent review by the authors.

The second caveat to this finding – and potentially to other of the above findings – is that leadership and other qualities not predicting academic success might, nevertheless, predict later success, in either getting a job or performing well as a lawyer. Future work based on this Article's data set will explore this possibility.

V. PRESCRIPTIONS: BRIEF NOTES ON POSSIBLE REFORMS TO HOW

SCHOOLS ADMIT AND PREPARE STUDENTS

How to reform law schools – both who should go to law school and what law schools should do differently – is a vast literature far beyond the scope of this one section of a primarily empirical Article. This Article's findings, though, do provide new evidence supporting some reforms and undercutting others. Readers likely will draw their own conclusions as to what prescriptions they might support or oppose more based on these findings, which is as it should be: empirical studies do not produce prescriptions by themselves; they simply provide evidence that, ideally, helps inform decisions about prescriptions. Because this section cannot do justice to the complex topic of assessing and reforming legal education, following is simply a brief discussion of three implications of this Article's findings that, in the authors' views, support or undercut various practices and proposed reforms of law schools.

A. Holistic Review, Given that No One Score, Credential, or Experience Possibly Can Predict Success or Failure by Itself

A key overall lesson of all the above findings is the need for a broadly holistic review of all applications – because no one variable, alone, is powerful enough to justify admitting or denying a particular applicant. Thus LSAT or UGPA "cutoffs" are ill-advised, even though those are two of the more powerful significant predictors of LGPA. Our dataset includes students who vary widely in LSAT and UGPA, because it combines four years of students from two schools with different LSAT and UGPA profiles. Even within that dataset, however, the seemingly large 13-point difference between 10th and 90th percentile LSAT (153 to 166) predicts only a 0.21 difference in LGPA. Among the binary group-membership variables (majors, work experiences, ethnicities, negative records, etc.), the largest plus and minus factors were akin to 6-10 LSAT points, meaning only a 0.10 to 0.16 difference in LGPA.

With almost no variable capable of predicting much more than one or two tenths of a point of difference in LGPA, treating any one applicant credential as dispositive is clearly a mistake. An applicant can make up for even a dozen fewer LSAT points with a high UGPA alone, or with some mix of other plusses, such as a positive-predicting major, work type, and duration of work experience.

B. The Heterogeneity of Candidates with Similar Backgrounds: The Need to Distinguish Apples from Slightly Different Apples

While no one factor is dispositive, law schools do have to make their best guesses as to who will and will not thrive in law school, and several factors are material plusses or minuses. But other findings show real heterogeneity among even high-performing groups: military experience predicts negatively, but with unusually high variance; STEM predicts positively but science or technology work experience predicts heightened risk of bottom-quarter LGPA. The hypothesized explanations for these positive and negative predictors hint at how to distinguish among high-variance population, such as military and science candidates.

As to military: because military experience predicts worst for 1L year, and likely derives in part from the difficulty some have adjusting to the more sedentary law student life, law schools could favor those military veterans (a) who already have shown academic success, *e.g.*, favor those with high-UGPA/low-LSAT over the reverse, or (b) who, unintuitively, held more sedate "desk jobs" in the military, such as intelligence analysts, paralegals in the Judge Advocate General's ("JAG") Corps, or those who worked on matters such as budgets and legal regulations.

As to those with science backgrounds: STEM majors' strengths (succeeding in courses with hard curves, etc.) are not discernibly counteracted by weaknesses from what such majors lack (*e.g.*, less reading-and-writing experience, and less of the pro-and-con dueling interpretations work that liberal arts or social science majors do), likely because the subset of STEM majors applying to law school is skewed (as shown by its nearly 50/50 gender split) toward those most comfortable with verbal work and grey-area interpretations. On the other hand, those with science work experience overpopulate the bottom quarter of LGPA, and while STEM majors do well in both their first year and cumulative LGPAs, our results suggest that they take time to develop their legal skills. According to Table 2, Models 1-2, while STEM is significant and positive for both 1L GPA and LGPA results, in the 1L GPA regression, the coefficient for STEM is 0.061, positive and significant at the 10% level, and in the LGPA regression, it is stronger and more significant -- 0.066 and significant at the 5% level. In evaluating those with science or technology backgrounds, law schools should scrutinize for skills useful to legal study that science training might under-provide: writing ability (as shown by the personal statement and LSAT unedited essay); performance in classes entailing reading and writing; and recommenders' statements, if any, about the applicant's verbal or writing skills.

More generally, the various positive or negative predictors should not be overinterpreted, because many are proxies for personal qualities, like maturity, that a particular candidate may or may not actually have. Teaching experience (a positive predictor) is best interpreted as a proxy for maturity and/or comfort with classroom learning, while negative criminal or disciplinary record (a negative predictor) is best interpreted as a proxy for immaturity or inability to handle institutional rules. But some with teaching experience show other signs of immaturity (*e.g.*, a shallow or self-aggrandizing personal statement) or discomfort with learning (*e.g.*, a middling-to-weak UGPA), while some with negative records show other signs of maturity and ability to play by the rules (*e.g.*, the passage of years since the negative record, or earning promotions in jobs they held for years and from which they received strong recommendation letters attesting to their maturity and responsibility).

In short, the significance of variables implies that certain qualities are plusses and minuses only on average, not for everyone; we examined the data in other ways (*e.g.*, for variance, or for top- and bottom-quarter odds) for hints of how each predictor might be a proxy for more fundamental qualities (maturity, etc.) that careful scrutiny of applications can assess more fully.

C. Helping Students Adjust – and Expanding the Talent Base by Doing So

This Article's findings support reform beyond simply making better admission decisions – such as reforms aimed at improving incoming students' adjustments to law school. As noted above, many of the positive and negative predictors reflect not pure talent level, but also (or instead) how well and how quickly various student types adjust to law school: some, like STEM or EAF majors, perform above-par but not as well 1L year; others, like those with military experience or people of color, perform well below par 1L year, which could yield discouragement that explains their less negative, but still below-par, cumulative LGPAs; still others, like those with teaching experience, perform above-par due possibly to their greater recent familiarity or comfort with the classroom setting.

To the extent that some students do worse not simply because of lesser talent, but because they have more of an adjustment to make, that supports improved early interventions to speed students' adjustment to the demands and culture of law school. Improved interventions would increase the fairness and accuracy of law school grades: if two students are equally talented, then the one with an academic, work, or cultural background less on-point for law school might fall behind 1L year; that falling behind would then leave LGPA inaccurately implying that this student is inferior in talent or lawyering potential to the equally talented student who simply had a more on-point background. Improved interventions therefore could help a law school admit students who project less positively, but could perform better if the school adopts effective interventions to speed their adjustment.

In this light, improved interventions could help a school find more talent, by letting it admit those who have weaker predictors, but who also have potential to improve with the right adjustment help. Some schools do have various such programs: spring semester 1L remedial courses for those who under-performed in their 1L year or fall semester, taught by legal writing faculty or by a professor with a dedicated role of providing additional support for student writing and legal analysis;[125] and/or pre-1L summer courses that either offer remediation for incoming students with low numerical predictors, or offer an opportunity for waitlisted candidates with low predictors to show their ability to perform in law

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[125] *See, e.g.*, *Legal Writing Faculty – Amy Griffin*, UNIV. OF COLO. L. SCH., http://lawweb.colorado.edu/profiles/profile.jsp?id=504 (last visited Feb. 26, 2015) ("Amy Griffin … [is] the law school's first Student Legal Writing Engagement Coordinator. Colorado Law added this new position to ensure that second- and third- year students continue to have access to comprehensive one-on-one legal writing support. Thus, in addition to teaching an advanced legal writing course, Amy works individually with students to continue the development of their legal writing skills throughout law school[,] … [on] law journal notes, seminar papers, independent research projects, externship assignments, and writing in the clinics.").

classes.[126] This Article provides evidence that such programs hold promise not only to increase the fairness of law school grading, but also to increase law schools' strategic ability to admit those who have lower predictors yet display potential – based on their work ethic, positivity, growth mindset, etc. – to overcome obstacles like facing a difficult adjustment, if given proper support.

VI. CONCLUSION

This Article's findings confirm certain longstanding law school admissions criteria, but call others into question, and support enhanced consideration of other criteria not traditionally given as much (or any) weight. While data-driven decision-making has entered the mainstream, it also faces pushback, raising concerns about treating people as numbers rather than holistically. This Article's findings, however, provide strong support for a more rather than less holistic approach, and a less rather than more numbers-driven approach, to law admissions. For example: LSAT is over-weighted compared to other, less univariate academic metrics such as a broad view of not only UGPA but college quality and college major; work experience truly is the positive that many believe it to be, with work in teaching especially positive; certain backgrounds make for quicker or slower adjustment to law study; and various markers of personal qualities – maturity, work ethic, and motivation – truly are significant positives or negatives. One novel aspect of this study is the way that it presents the key results in two ways. Like most traditional empirical studies, the results are presented using regression coefficients and degrees of significance; but also, the results are presented in comparison to LSAT points, to provide more intuitive explanations to non-empirical audiences.

That significant findings and take-home lessons for law student selection resulted from this Article's data-gathering supports further such studies. Further work can assess, for example, what qualities, both preceding and during law school, predict which law students will earn full-time jobs, higher-paying jobs, and bar passage. The increased maintenance in electronic form of law applicant data, law school grades, and law student employment data can facilitate such work, but with effort still required to code the data not maintained in any electronic form

126 "Some law schools offer programs where admission is contingent upon the successful completion of a pre-enrollment program" just before 1L year starts. Law School Admission Council, *Conditional Admission Programs*, LAW SCHOOL ADMISSION COUNCIL (June 12, 2014), http://www.lsac.org/jd/diversity-in-law-school/racial-ethnic-minority-applicants/conditional-admission-programs (listing 23 such programs); *e.g.*, *NSU Law Professor Receives Patent for an Alternative Admission Model Program for Legal Education*, Nova Southeastern Univ. L. Ctr. (May 27, 2014), http://nsunews.nova.edu/nsu-law-professor-receives-patent-for-an-alternative-admission-model-program-for-legal-education ("AAMPLE®, the Alternative Admissions Model Program[,] … [is] an additional method of identifying candidates for admission …. [A]pplicants are enrolled in two [courses] …. replicat[ing] an appropriate portion of an equivalent regular J.D. offering …. The primary purpose … [is] evaluating the capabilities of prospective students.").

(*e.g.*, items on students' resumes), to code data maintained electronically in textual form (*e.g.*, law students' courses and activities), and to merge disparate databases (*e.g.*, in admissions, registrar, and career services offices). Law schools may be understandably reluctant to devote substantial staffing resources to such efforts, to let researchers who are strangers to the school access confidential data (applications, grades, disciplinary problems, etc.), or both. Such entirely valid concerns are why, to obtain a dataset of two schools, the authors had to ask eleven schools to join this study; nine schools other than Colorado and Case Western declined. Given that this Article offers findings law schools may find useful, the data-gathering, coding, and statistical analysis effort seems a worthwhile use of school staffing resources and researcher effort. Thankfully, the data-gathering and coding effort required for this Article produced a data set that will allow further analyses and publications as to employment and bar examination outcomes in the future.

Appendix

Table 4: Summary Statistics for Indicator Variables

Indicator Variables	*N*	*As Percent of Dataset*
Ethnicity		
African American	59	4%
Latino/a	45	3%
Asian American	142	10%
Native American	15	1%
Employment duration		
1-3 years	409	28%
4-9 years	112	8%
10+ years	35	2%
Employment type		
Teaching	75	5%
Legal	100	7%
Business	111	8%
Technology	124	9%
Military	34	2%
Public Service	70	5%
College major		
Science, Tech., Engineering, Math (STEM)	237	16%
Economics, Accounting, Finance (EAF)	166	12%
Psychology, Sociology, Anthropology	233	16%
Art, Music, Drama	38	3%
Environmental Sciences	33	2%
Liberal Arts, History	472	33%
Other factors		
No work experience & rising college GPA	252	18%
Criminal history	72	5%
Graduate degree	185	13%
University of Colorado Law Student	571	40%
College leadership	118	8%
Gender male	797	55%

NOTE: Summary statistics of indicator variables – the number of observations in each sample and the relative percent in the dataset.

Table 5: OLS Regression: Dependent Variable is LGPA

	(1a)	*(1b)*	*(1c)*	*(1d)*	*(1e)*	*(1f)*
Traditional Factors						
Law School Admissions Test (LSAT)	0.014*** (8.51)	0.011*** (6.54)	0.012*** (6.77)	0.011***(6.53)	0.010*** (6.10)	0.016*** (9.31)
Adjusted LSAT College Median (LCM)	0.003*** (3.39)	0.004*** (3.58)	0.003*** (3.09)	0.003** (3.11)	0.003** (3.05)	0.003*** (3.55)
Adjusted Undergraduate GPA (UGPA)	0.215*** (10.34)	0.191*** (9.36)	0.191*** (9.33)	0.191*** (9.30)	0.199*** (9.64)	0.272*** (12.44)
Ethnicity						
African American		-0.216*** (5.12)	-0.208*** (4.92)	-0.204*** (4.81)	-0.204*** (4.83)	-0.155*** (3.77)
Latino/a		-0.251*** (5.48)	-0.251*** (5.48)	-0.248*** (5.40)	-0.244*** (5.33)	-0.148*** (3.29)
Asian American		-0.161*** (5.89)	-0.162*** (5.90)	-0157*** (5.71)	-0.161*** (5.86)	-0.154*** (5.81)
Native American		-0.295*** (3.78)	-0.289*** (3.70)	-0.288*** (3.69)	-0.290*** (3.71)	-0.173** (2.28)
Employment duration						
1-3 years			-0.026 (1.40)	-0.030 (1.43)	-0.020 (1.35)	0.032 (1.47)
4-9 years			-011 (0.36)	-0.010 (0.26)	0.004 (0.11)	0.109** (2.88)
10+ years			-0.128** (2.39)	-0.142** (2.45)	-0.136** (2.34)	0.014 (0.25)
Employment type						
Teaching				0.086** (2.26)	0.084** (2.22)	0.082+ (2.20)
Legal				-0.004 (0.12)	-0.001 (0.03)	0.022 (0.69)
Business				-0.023 (0.69)	-0.034 (1.04)	-0.023 (0.75)
Technology				0.009 (0.31)	-0.027 (0.81)	-0.05 (1.55)
Military				-0.091+ (1.66)	-0.097+ (1.78)	-0.119+ (2.25)
Public Service				0.037 (0.96)	0.038 (1.00)	0.043 (1.17)
College major						
Science, Tech., Engineering, Math (STEM)					0.081** (3.15)	0.066** (2.65)
Economics, Accounting, Finance (EAF)					0.062** (2.36)	0.058** (2.30)
Psychology, Sociology, Anthropology					0.003 (0.14)	-0.006 (0.30)
Art, Music, Drama					-0.015 (0.32)	-0.038 (0.80)
Environmental Sciences					-0.043 (0.78)	0.022 (0.42)
Liberal Arts, History					0.018 (1.00)	-0.001 (0.08)
Other factors						
No work experience & rising college GPA						0.033 (1.45)
Criminal history						-0.119** (3.39)
Graduate degree						0.030 (1.22)
University of Colorado Law student						-0.209*** (10.12)
College leadership						0.018 (0.67)
Gender male						0.014 (0.89)
Constant	-0.317 (1.30)	0.302 (1.06)	0.259 (0.90)	0.313 (1.08)	0.380** (1.31)	-0.821** (2.70)
Adjusted R^2	0.15	0.19	0.20	0.20	0.20	0.26
Observations	1419	1419	1419	1419	1419	1419

NOTES: Absolute value of z-statistics in parentheses. +p<0.10; ** p<0.05; ***p<0.01.

Table 6: OLS Regression: Dependent Variable is 1L GPA

	(2a)	*(2b)*	*(2c)*	*(2d)*	*(2e)*	*(2f)*
Traditional Factors						
Law School Admissions Test (LSAT)	0.028*** (12.73)	0.024*** (10.62)	0.025*** (10.77)	0.024*** (10.48)	0.024*** (10.18)	0.030*** (12.63)
Adjusted LSAT College Median (LCM)	0.004** (2.78)	0.004** (2.90)	0.003*** (2.57)	0.003** (2.58)	0.003*** (2.52)	0.004** (2.98)
Adjusted Undergraduate GPA (UGPA)	0.262*** (9.66)	0.235*** (8.68)	0.233*** (8.62)	0.233** (8.60)	0.240*** (8.78)	0.328*** (11.22)
Ethnicity						
African American		-0.254*** (4.70)	-0.244*** (4.48)	-0.240*** (4.42)	-0.241*** (4.43)	-0.170** (3.35)
Latino/a		-0.267*** (4.54)	-0.263*** (4.47)	-0.260*** (4.42)	-0.258*** (4.39)	-0.148** (2.52)
Asian American		-0.137*** (3.88)	-0.138*** (3.91)	-0.134*** (3.77)	-0.137*** (3.85)	-0.130*** (3.77)
Native American		-0.308*** (3.20)	-0.302** (3.13)	-0.310** (3.21)	-0.318** (3.28)	-0.188** (1.97)
Employment duration						
1-3 years			-0.040+ (1.73)	-0.039 (1.46)	-0.035 (1.30)	0.032 (1.16)
4-9 years			-0.036 (0.94)	0.013 (0.28)	0.007 (0.16)	0.110** (2.49)
10+ years			-0.096 (1.44)	-0.090 (1.25)	-0.085 (1.18)	0.081 (1.11)
Employment type						
Teaching				0.090+ (1.88)	0.084+ (1.74)	0.086+ (1.80)
Legal				-0.012 (0.29)	-0.01 (0.23)	0.015 (0.35)
Business				-0.030 (0.69)	-0.036 (0.86)	-0.025 (0.61)
Technology				-0.019 (0.49)	-0.05 (1.18)	-0.077+ (1.85)
Military				-0.198** (2.88)	-0.206** (2.99)	-0.231** (3.43)
Public Service				0.065 (1.33)	0.062 (1.27)	0.068 (1.44)
College major						
Science, Tech., Engineering, Math (STEM)					0.076** (2.30)	0.061+ (1.90)
Economics, Accounting, Finance (EAF)					0.036 (1.07)	0.032 (0.97)
Psychology, Sociology, Anthropology					0.019 (0.66)	0.011 (0.38)
Art, Music, Drama					-0.051 (0.77)	-0.084+ (1.33)
Environmental Sciences					-0.054 (0.76)	0.012 (0.17)
Liberal Arts, History					0.037 (1.55)	0.016 (0.70)
Other factors						
No work experience & rising college GPA						0.053+ (1.82)
Criminal history						-0.137** (2.99)
Graduate degree						0.037 (1.16)
University of Colorado Law student						-0.225*** (8.33)
College leadership						0.019 (0.51)
Gender male						0.015 (0.72)
Constant	-2.885*** (7.57)	-2.090*** (5.34)	-2.190*** (5.52)	-2.080*** (5.26)	-2.041*** (5.12)	-3.470*** (8.21)
Adjusted R^2	0.20	0.23	0.23	0.23	0.23	0.28
Observations	1317	1317	1317	1317	1317	1317

NOTES: Absolute value of z-statistics in parentheses. +p<0.10; ** p<0.05; ***p<0.01.

Table 7: Model 3 and 4 Results, Logistic Regression, Dependent Variable is Having an LGPA in either the Top (Q1) or Bottom (Q4) Quarter of the Class

	Model 3 *Odds Ratio of Being in Top Quarter (Q1)*	*Model 4* *Odds Ratio of Being in the Bottom Quarter (Q4)*
Traditional factors		
Adjusted LSAT College Median (LCM)	1.04*** (3.31)	0.96*** (3.48)
Adjusted Undergraduate GPA (UGPA)	6.80*** (8.86)	0.17*** (8.86)
LSAT	1.12*** (6.62)	0.921*** (5.28)
Ethnicity		
African American	0.45 (1.39)	3.62*** (3.83)
Latino/a	0.23+ (1.99)	1.86+ (1.83)
Asian American	0.38*** (3.31)	0.38*** (3.31)
Native American	1.34 (0.41)	2.76+ (1.76)
Employment duration		
1-3 years	1.30 (1.40)	0.673** (2.02)
4-9 years	2.78*** (3.23)	0.395*** (2.66)
10+ years	0.69 (0.63)	0.85 (0.32)
Employment type		
Teaching	1.27 (0.78)	0.58 (1.42)
Legal	0.78 (0.82)	0.78 (0.86)
Business	0.77 (0.89)	0.90 (0.36)
Technology	0.71 (1.20)	1.83** (2.13)
Military	0.67 (0.79)	3.09** (2.52)
Public Service	1.48 (1.31)	1.27 (0.72)
College major		
Science, Tech., Engineering, Math (STEM)	1.71** (2.53)	0.761 (1.22)
Economics, Accounting, Finance (EAF)	1.30** (1.21)	0.84 (0.75)
Psychology, Sociology, Anthropology	1.19 (0.93)	1.20 (0.97)
Art, Music, Drama	1.08 (0.21)	1.08 (0.21)
Environmental Sciences	1.27 (0.59)	1.24 (0.47)
Liberal Arts, History	1.26 (1.48)	1.29 (1.61)
Other factors		
No work experience & rising college GPA	1.33 (1.47)	0.66+ (1.67)
Criminal history	0.44** (2.15)	1.96** (2.46)
Graduate degree	1.16 (0.69)	0.68+(1.67)
University of Colorado Law Student	0.27*** (6.97)	3.47*** (6.67)
College leadership	1.07 (0.30)	0.85 (0.66)
Gender male	1.13 (0.91)	0.72** (2.3)
Adjusted R^2	0.15	0.16
Observations	1419	1419

NOTES: Absolute value of z-statistics in parentheses. +p<0.10; ** p<0.05; ***p<0.01.

Table 8: Model 5 Results, OLS Regression using only "Splitters" (High-LSAT and Low-GPA or Vice-Versa). Dependent Variable is LGPA

	Model 5
Traditional factors	
Adjusted LSAT College Median (LCM)	0.005*** (3.32)
Index	0.016*** (7.00)
Splitter category	
Top 50% LSAT, bottom 50% GPA	-0.052** (2.21)
Ethnicity	
Asian American	-0.176*** (5.35)
Employment duration	
1-3 years	-0.017***(5.35)
4-9 years	0.106** (2.27)
Employment type	
Teaching	0.079+ (1.65)
Legal	-0.005 (0.12)
Business	-0.077 + (1.81)
Technology	-0.116** (2.71)
Public Service	0.052 (1.05)
College major	
Science, Tech., Engineering, Math (STEM)	0.072** (2.18)
Economics, Accounting, Finance	0.037 (1.07)
Psychology, Sociology, Anthropology	0.030 (0.97)
Liberal Arts, History	-0.011 (0.48)
Other factors	
No work Experience & rising college GPA	-0.003 (0.11)
Criminal history	-0.066 (1.47)
Graduate degree	0.067+ (1.88)
University of Colorado Law Student	-0.173*** (5.82)
College leadership	0.026 (0.67)
Gender – male	0.002 (0.12)
Constant	-0.607 (1.25)
Adjusted R^2	0.13
Observations	732

NOTES: Absolute value of z-statistics in parentheses. +p<0.10; ** p<0.05; ***p<0.01.

Table 9: Summary Statistics for Entire Sample and for Selected Dichotomous Variables

		Mean			*LGPA*		
	Observations	*UGPA*	*LSAT*	*Index*	*Mean*	*Std. Dev.*	*Variance*
Entire dataset	1419	3.43	159	194	3.18	0.009	0.0001
<u>Selected dichotomous Variables:</u>							
Top 25% GPA/bottom 25% LSAT	80	3.81	23	192	3.17	0.033	0.0011
Top 25% LSAT/bottom 25% GPA	114	3.01	165	195	3.18	0.027	0.0007
Majored in STEM	23	3.34	161	194	3.22	0.022	0.0005
Majored in EAF	166	3.42	160	194	3.23	0.024	0.0006
No work experience	814	3.44	159	193	3.19	0.011	0.0001
Work: 1-3 years	400	3.43	160	195	3.18	0.017	0.0003
Work: 4-9 years	111	3.41	162	196	3.21	0.036	0.0013
Work: 10+ years	34	3.49	162	196	3.07	0.055	0.003
Work: in Teaching	73	3.47	162	197	3.30	0.036	0.0013
Work: in Tech Field	120	3.36	161	194	3.18	0.030	0.0009
Work: in Military	34	3.47	160	194	3.08	0.068	0.0046
Graduate degree	175	3.40	160	194	3.24	0.027	0.0007
Criminal history	72	3.34	159	193	3.05	0.042	0.0018
No work experience & Rising GPA	246	3.25	158	191	3.15	0.021	0.0004

NOTES: This table provides the number of observations, in addition to the mean and LGPA summary statistics for the entire dataset of two schools combined and for selected dichotomous variables.

Table 10: Summary Statistics for Law Schools

	LSAT			*UGPA*		
	Median	*Top 25%*	*Bottom 25%*	*Median*	*Top 25%*	*Bottom 25%*
University of Colorado Law School	163	164	160	3.64	3.74	3.43
Case Western University Law school	158	158	157	3.39	3.54	3.29
Combined law schools	159	159	158	3.48	3.62	3.35

NOTES: This table presents LSAT and UGPA summary statistics for the two individual law schools and for the two law schools combined.